

Social Media, News Consumption, and Polarization: Evidence from a Field Experiment

Ro'ee Levy

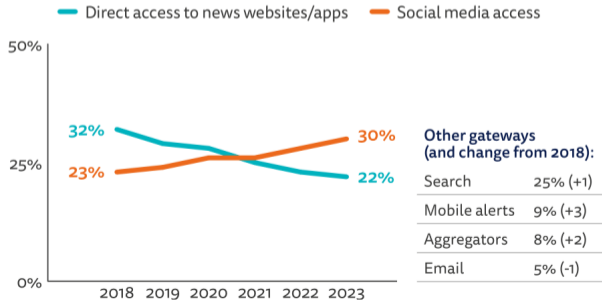
Tel Aviv University

BMI's 9th Annual Conference
May 2024

Motivation: Concerns Over Social Media

- Consumption of news through social media is increasing
 - 12% (2008) → 69% (2023)
 - Social media is the most important source for online news

PROPORTION THAT SAY EACH IS THEIR MAIN WAY OF GETTING NEWS ONLINE (2018-2023) - ALL MARKETS



Motivation: Concerns Over Social Media

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 - 12% (2008) → 69% (2023)
 - Social media is the most important source for online news

- Pro-attitudinal news → polarization?
 - News based on social network
 - News based on algorithm
 - Users personalize their feed

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 - Social media is the most important source for online news
- Pro-attitudinal news → polarization?
 - News based on social network
 - News based on algorithm
 - Users personalize their feed
- Could lead to policies decreasing welfare
- May threaten democracy



Overview

- **Research questions**

1. How does social media affect news consumption?
2. Does exposure to news on social media affect political opinions and polarization?

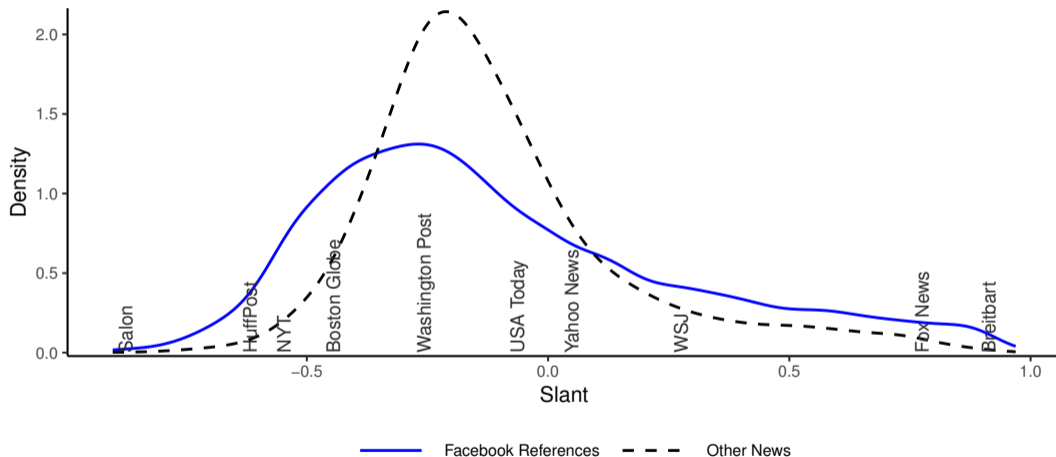
- **Approach**

- Descriptive - collect rich news consumption data
 - Social media associated with extreme, pro-attitudinal news
- Causal - field experiment varying social media feeds
 - Analyze chain of effects: FB exposure, website visits, political opinions and attitudes

- **Preview**

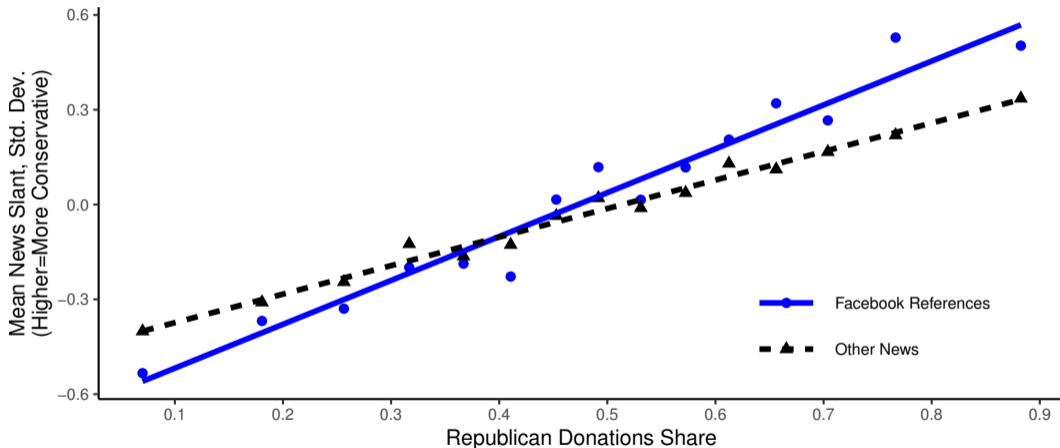
- The social media feed substantially affects news consumption
- Facebook's algorithm decreases exposure to counter-attitudinal news
- Counter-attitudinal news decreases polarization

What is consumed through social media? (1)



Comscore data. Slant based on Bakshy et al. (2015). Constant sample of users who consumed news both through Facebook and other means.

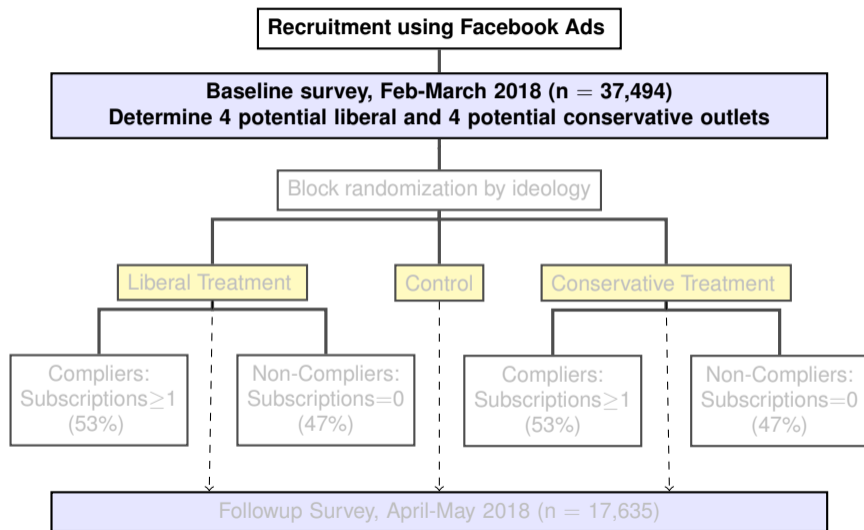
What is consumed through social media? (2)



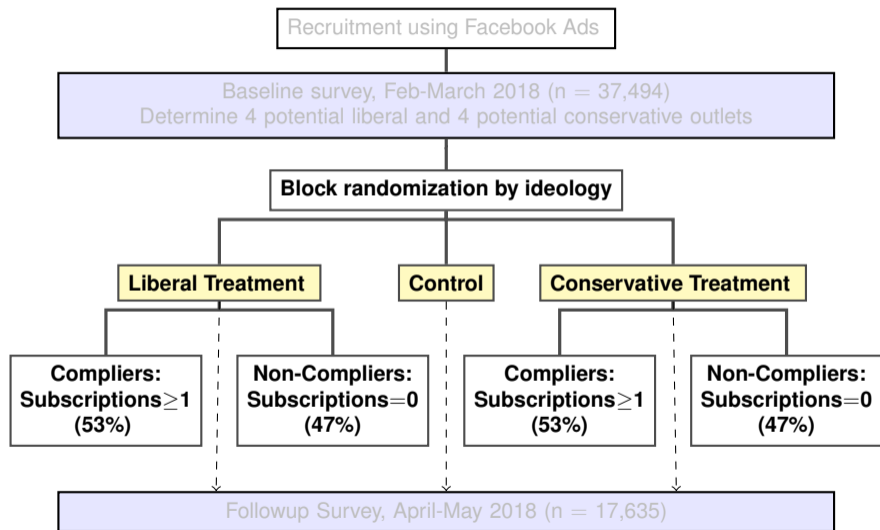
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Design

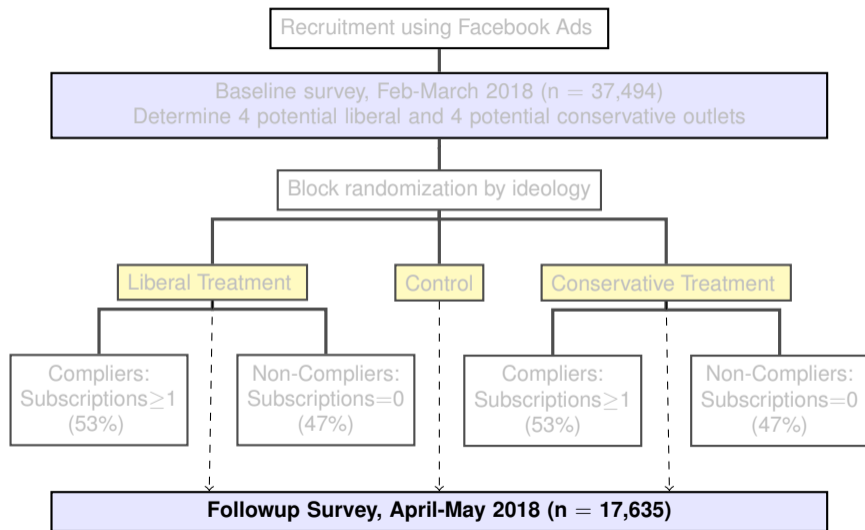
Design Overview



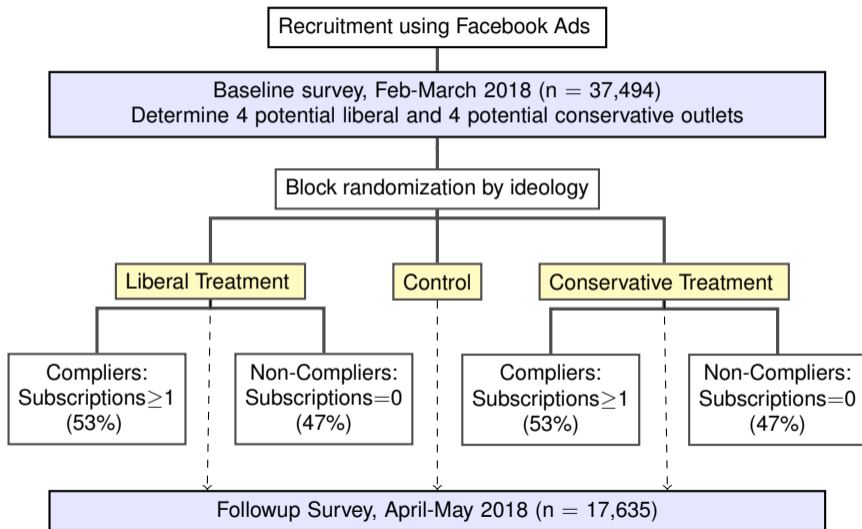
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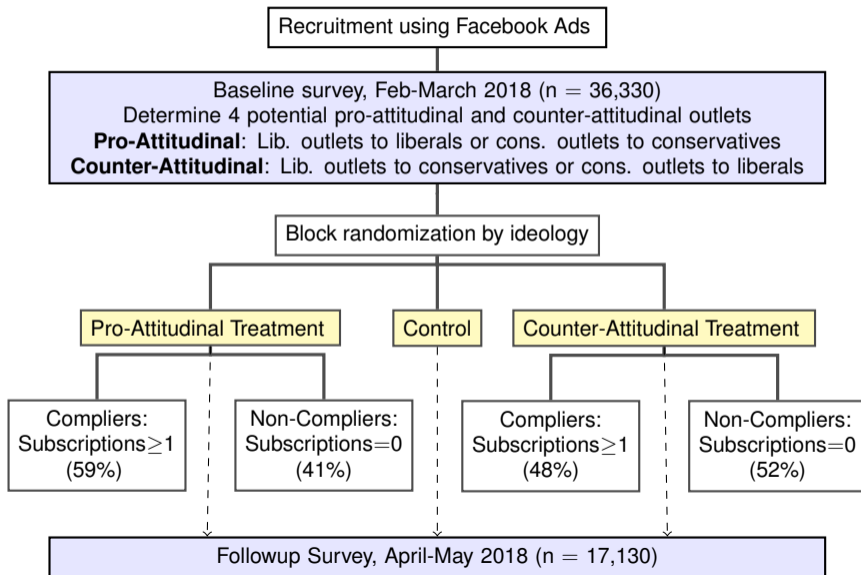
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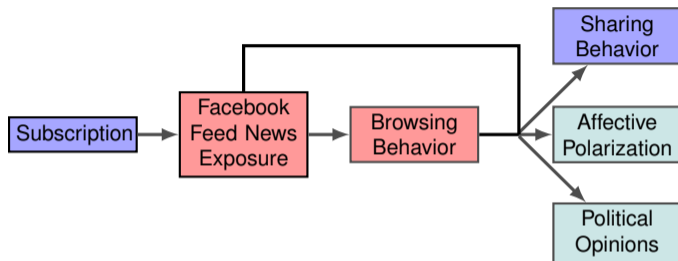
Design Overview



Research Design Benefits

1. High external validity
 - Intervention similar to common social media nudges
 - Natural behavior in every other aspect:
Media content, platform algorithms and individual decisions
 - Popular news outlets in dominant social network
2. Large N to detect small effects
3. Randomizing subscriptions to outlets instead of articles
 - Medium-run effect, priming less likely to affect results
4. Rich data on news exposure and consumption

Data: Causal Chain of Media Effects



Data sources

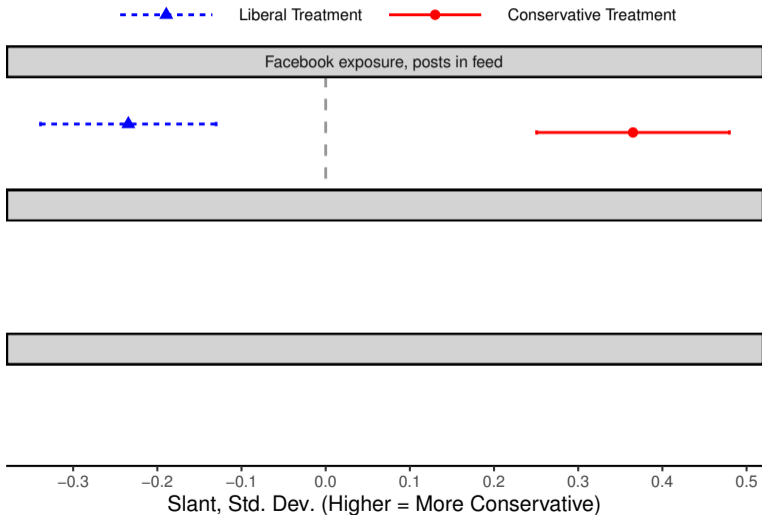
- FB data: subscriptions (N=37,494) and post sharing (N=34,592)
 - Facebook app Facebook Data Screenshots
- Extension data: exposure and browsing behavior (N=1,835)
 - Chrome extension Extension Data Screenshots
- Survey data: political opinions and attitudes (N=17,635)
 - Endline survey, analysis pre-registered Survey Data

Results

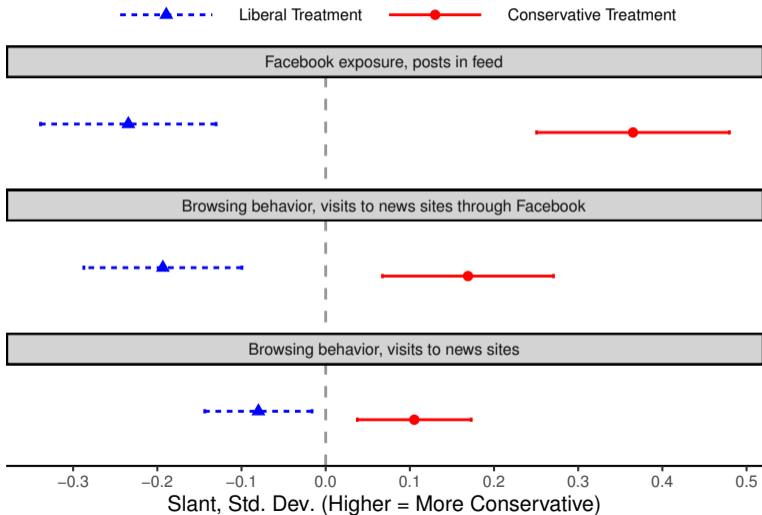
Results

- Individuals engage with new outlets when nudged
- The feed substantially affects online news consumption
- No evidence that outlets' slant affect political opinions
- Counter-attitudinal news decreases affective polarization
- Algorithm limits exposure to counter-att. posts

Effect of the Treatment on News Slant



Effect of the Treatment on News Slant



Participants in Post Sharing and Extension Subsamples ($N \leq 1,699$)

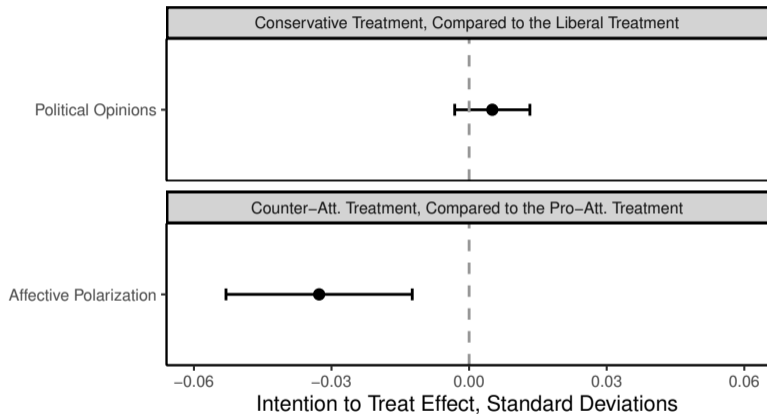
Followup Survey Primary Outcomes

- Political Opinions Index (\uparrow = More conservative)
 - 20 questions on issues covered during the study period
 - March for Our Lives, Stormy Daniels, Mueller investigation, etc.
 - Compare conservative and liberal treatments
- Affective Polarization Index (\uparrow = More hostility) (Iyengar et al., 2019)
 - 5 questions, measuring attitudes toward political parties
 - Feeling thermometer
 - Difficult to see things from Dem/Rep point of view
 - Important to consider the perspective of Dem/Rep (*Willer*)
 - Dem/Rep party has good ideas
 - Son or daughter married other party
 - Compare pro- and counter-attitudinal treatments

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Treatment Effects on Primary Outcomes



Participants in Endline Survey Subsample (N=17,130-17,635)

- Effect on attitudes, not political opinions; in line with long-term trend

Treatment Effect Magnitude

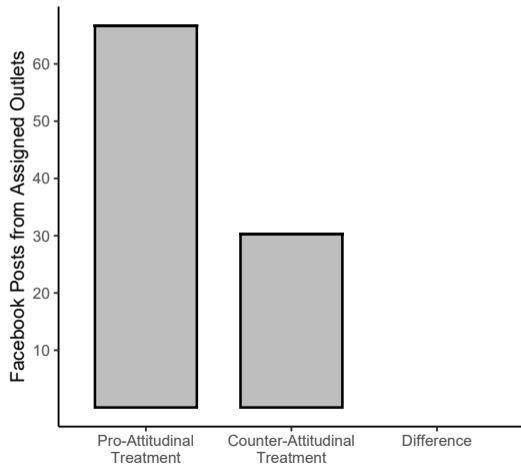
- Focus on feeling thermometer questions (0-100 degrees)
 - Feeling toward own party - feeling toward opposing party
- Counter vs. pro-attitudinal treatment
 - ITT: -0.58
 - TOT (compliance instrument with treatment): -0.96
- Benchmarks
 - Secular trend 1996-2016 (ANES): 3.83-10.52
 - One month Facebook disconnection (Allcott et al., 2020): -2.09

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Differential Exposure to Matching vs. Opposing Posts

Why is there less exposure to posts from the counter-attitudinal outlets?



Participants for whom FB posts and subscriptions are observed for at least 2 weeks (N=1,059)

Explaining Differential Exposure

- The exposure of individual i to posts shared by outlet j :

$$E_{ij} = S_{ij}P_{ij}U_i$$

- $S_{ij} \in \{0, 1\}$ is i 's subscription to outlet j (“selective exposure”)
- P_{ij} is posts supplied from j to i conditional on subscription (“filter bubble”)
- U_i is the total number of posts i observed (usage)

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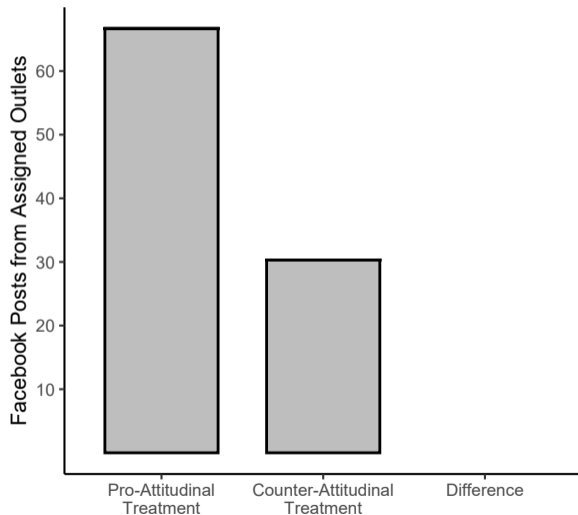
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$$\Delta E = \underbrace{S_{\Delta} * P_C * U_C}_{\text{Subscriptions}} + \underbrace{S_C * P_{\Delta} * U_C}_{\text{Platform Algorithms}} + \underbrace{S_C * P_C * U_{\Delta}}_{\text{Platform Usage}} + \underbrace{\dots}_{\text{Combinations}}$$

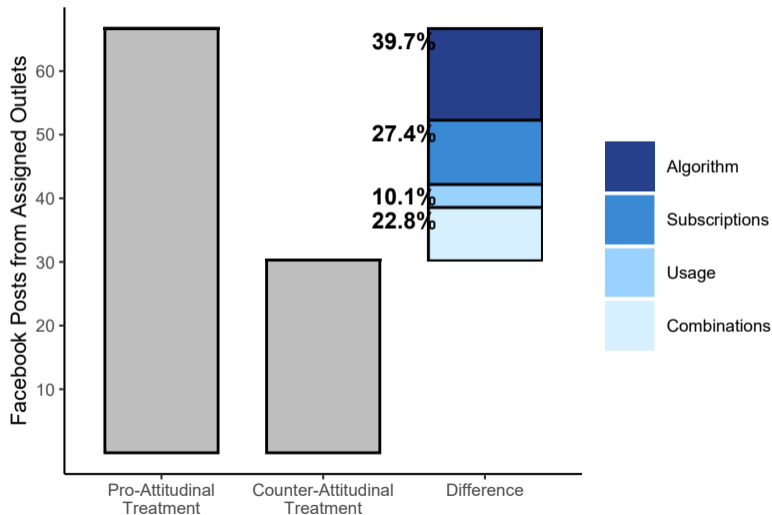
- S_C is subscriptions in the counter-attitudinal treatment
- S_{Δ} is the difference in subscriptions between the treatments

Differential Exposure to Matching vs. Opposing Posts



Participants for whom FB posts and subscriptions are observed for at least 2 weeks (N=1,059)

Differential Exposure to Matching vs. Opposing Posts



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Conclusions

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1. FB algorithms \Rightarrow \downarrow Exposure to counter-attitudinal news
 - Feed affects news consumption
 - Growing importance as “pointcasting” replaces broadcasting
2. \uparrow Counter-attitudinal news \Rightarrow \downarrow affective polarization
 - Changes in media habits may explain increase in polarization
 - Social media algorithms may increase partisan hostility
 - Minimal effect on political opinions
 - Could still affect policy outcomes, trust and accountability
3. Individuals willing to engage with counter-attitudinal news
 - Policies diversifying content in social media can be effective

Thank You

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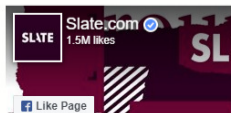
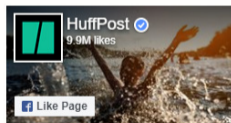
Design Preview

- Randomly assign participants to
 - Liberal treatment
 - Conservative treatment
 - Control group

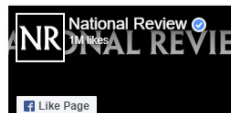
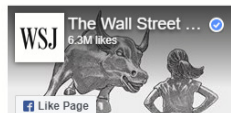
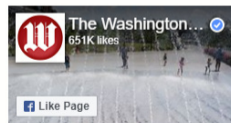
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Liberal Treatment



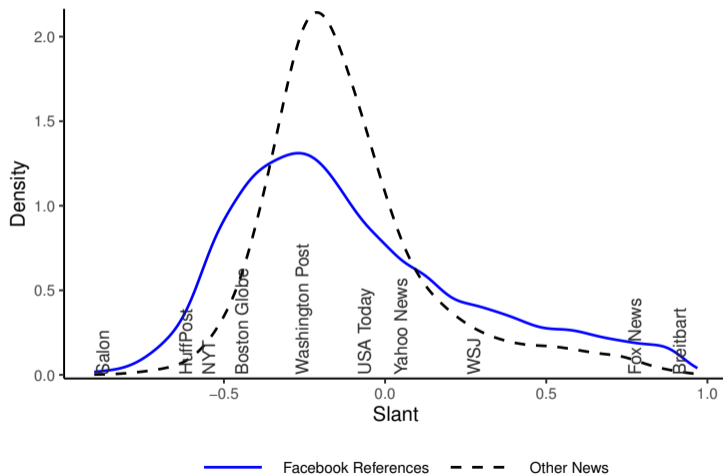
Conservative Treatment



Literature and Contribution

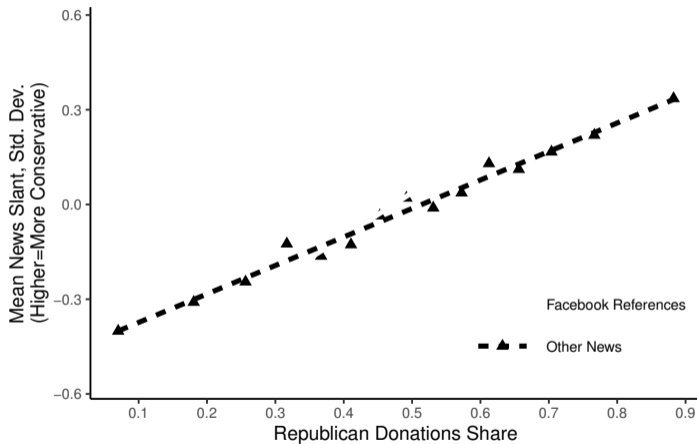
- **Supply and demand of online news** (Allcott and Gentzkow, 2017; Flaxman et al., 2016; Gentzkow and Shapiro, 2011; Guess et al., 2017), **algorithmic bias** (Bakshy et al., 2015; Sunstein, 2017; Tufekci, 2015)
 - Algorithms increase exposure to pro-att. news
- **Social media, pro-attitudinal news and polarization** (Allcott et al., 2020; Boxell et al., 2017; Bursztyn et al., 2019; Enikolopov et al., 2020; Lelkes, 2016)
 - First experimental evidence that pro-att. news increases affective polarization, compared to counter-att. news
- **Media and persuasion** (Bail et al., 2018; Chen and Yang, 2019; Chiang and Knight, 2011; Coppock et al., 2018; DellaVigna and Kaplan, 2007; Gentzkow et al., 2011; Gerber et al., 2009; Martin and Yurukoglu, 2017)
 - Exploit social media's infrastructure to randomize subscriptions to news outlets in a natural setting

Social Media Associated with More Extreme News



Source: Analysis of 2017 Comscore data. Slant based on Bakshy et al. (2015). Constant sample of users who consumed news both through Facebook and other means.

Social Media Associated with Pro-Attitudinal News



Source: Analysis of 2017 Comscore data. Slant based on Bakshy et al. (2015). Republican donations based on 2016, 2018 FEC donation data. Constant sample of users who consumed news both through Facebook and other means.

Balance and Attrition

- Sample is balanced

Baseline: Pro vs Counter Treatments

Baseline: Liberal vs Conservative Treatments

- Differential attrition in followup survey (51% vs 54%)

- No significant or meaningful differences between control group and treatment arms on observables
- No differential attrition between the two treatment arms \Rightarrow
 - Compare treatment arms when analyzing effect on beliefs
- Not a concern with extension or Facebook data

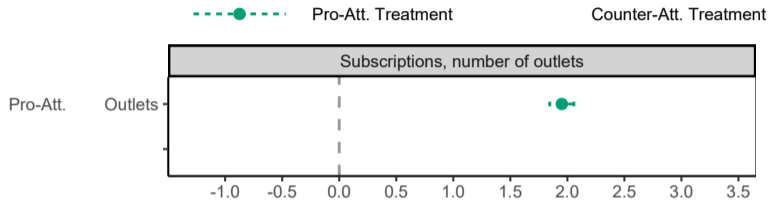
Followup: Pro vs Counter

Followup: Liberal vs Conservative

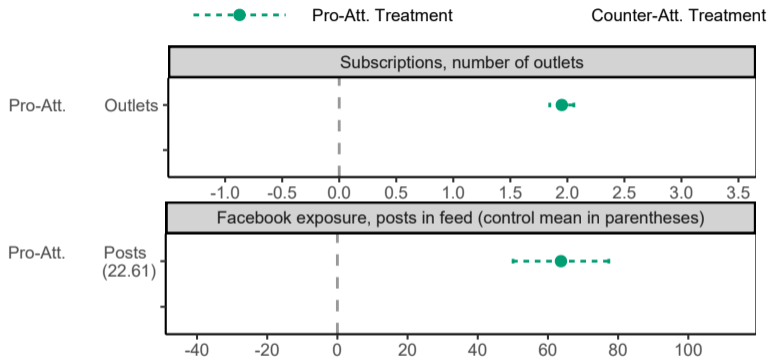
Compliers

Compliance Regressions

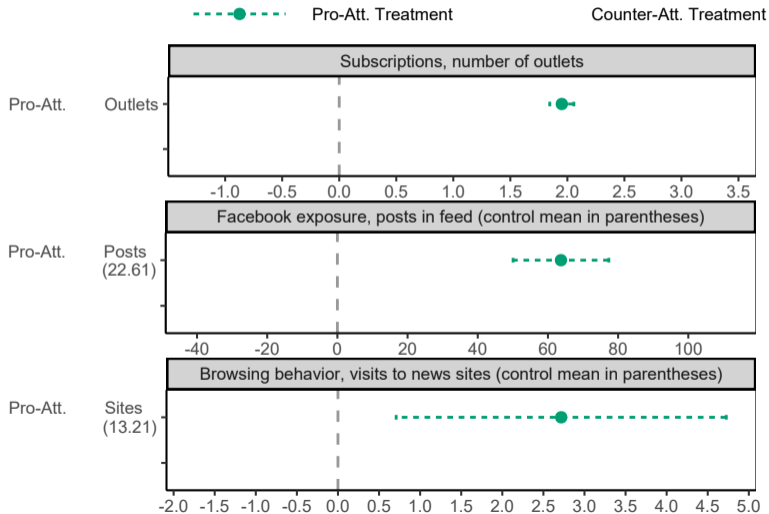
ITT After Two Weeks: Pro vs. Counter Attitudinal



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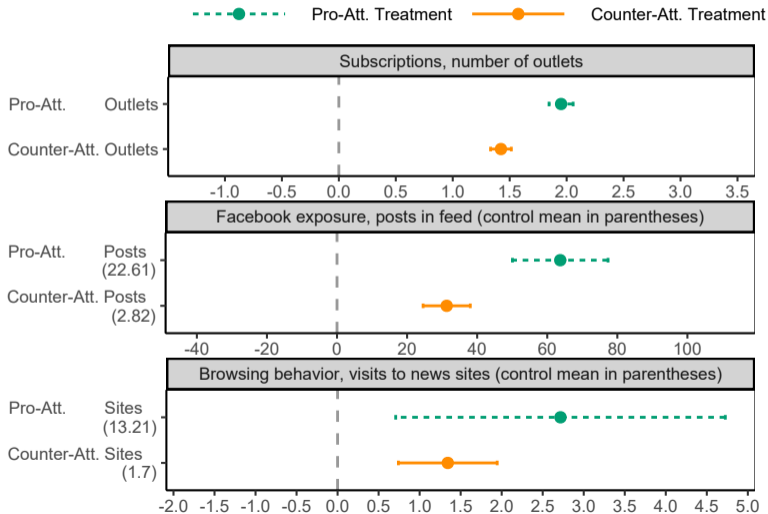


ITT After Two Weeks: Pro vs. Counter Attitudinal



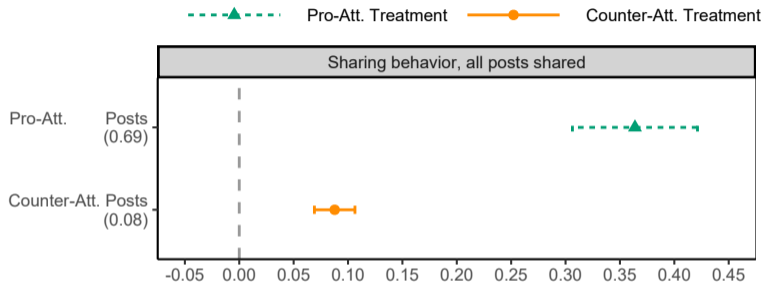
Participants in Post Sharing and Extension Subsamples with an ideological leaning (N=1,648)

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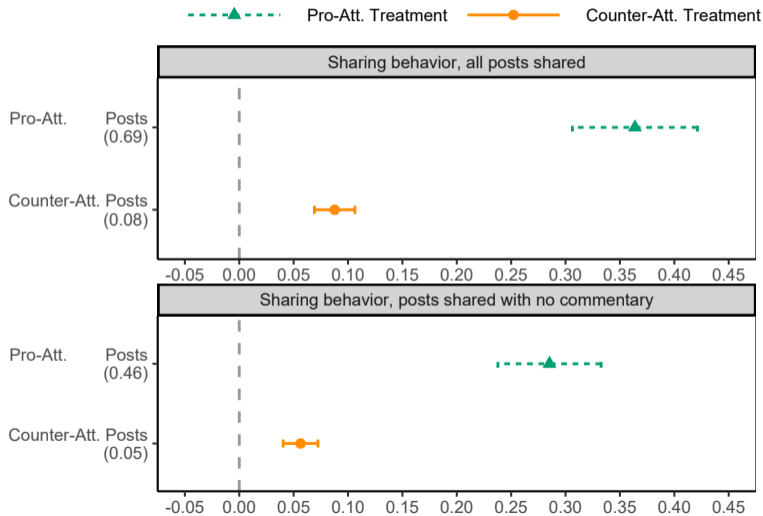


Participants in Post Sharing and Extension Subsamples with an ideological leaning (N=1,648)

Shared Posts



Shared Posts



Participants in Post Sharing Subsample (N=33,532)

Effect of News Exposure on Attitudes

1. Share of counter-attitudinal posts

- Definition: $\frac{\text{counter-att. posts}}{\text{counter-att. posts} + \text{pro-att. posts}}$
- $Polarization_i = CounterShare_i + X_i + \varepsilon_i$
 - where $CounterShare_i$ instrumented with treatment
- Magnitude: \uparrow one std. dev. \Rightarrow \downarrow polarization by 0.13 std dev
 - Control group cross-sectional correlation: 0.38 std dev
 - Estimated effect of exposure: 34%

2. Congruence scale

- Definition: $\text{slant} * \text{sign}(\text{ideology})$
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Counterfactuals

1. Equal share of pro and counter-attitudinal posts

- Method
 - Effect of 1% share on feeling thermometer (IV): 0.12 degrees
 - Increase by difference between balanced feed (50%) and control group mean (17%)
- Result: **3.94** degrees

2. FB share of counter-attitudinal = browsing share

- Method:
 - Increase by control group difference between browsing share of counter-att. outlets (19%) and Facebook feed share (17%)
- Result: **0.24** degrees
- Robustness based on congruence scale: 3.43, 0.62 degrees

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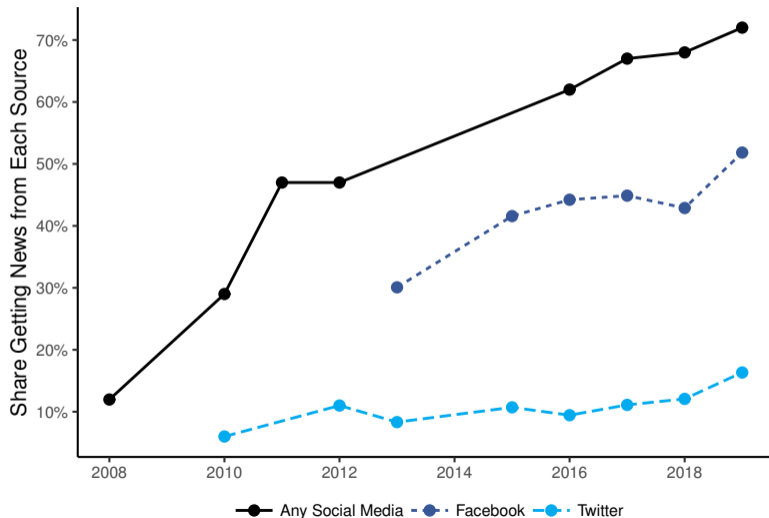
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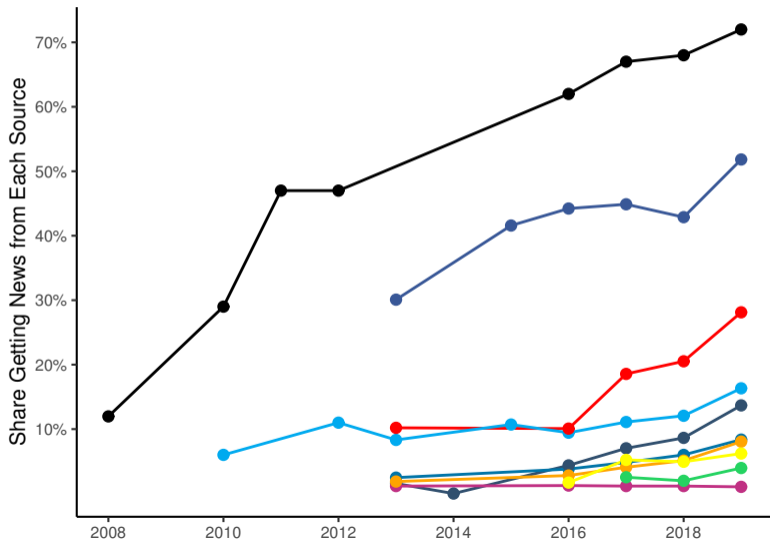
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US Social Media News Consumption

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Source: PEW Media Consumption Survey, News Use Across Social Media.

US Social Media News Consumption

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Liberal Treatment

Mer Zoran
about 4 months ago

Listen to an historian - vaccination!




THEGEMINIPICT.CO.UK

Vaccination: A brief and sadly necessary history ...
The privilege many 21st-century parents think they have ...

👍 2 Comment Share

The New York Times
about 2 years ago

In The New York Times Opinion Section, former Supreme Court Justice John Paul Stevens writes: "Demonstrations should seek more effective and more lasting reform. They should demand a repeal of the Second Amendment."



NYTIMES.COM

Opinion | John Paul Stevens: Repeal the Second ...
Pictured: A rifle from the 18th century, when the Second Am...

👍 10K 🗨️ 1.4K ➦ 4.5K

Ambika
about 7 months ago

Saturdays mean getting away with someone fun. Now through August 30th, buy one ticket and bring a friend for free on Saturday trips from Boston to Norfolk, and all stops in-between.



TURN SATURDAY INTO A GETAWAY

WWW.AMBIKA.COM

BUY ONE TICKET. GET ONE FREE

👍 1 Comment ➦ 1

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Vaccination: A brief and sadly necessary history ...
The privilege many 21st-century parents think they have ...

👍 2 Comment Share

The Washington Times
about 2 years ago

"If you're going to allow students to walk up and get out of class without penalty, then you have to allow any group of students that wants to protest."



Julianne Borzell
3:10
On Leave after Strikeline

WASHINGTONTIMES.COM

Calif. teacher on leave after questioning whether ...
A California high school teacher was placed on paid adminis...

👍 417 🗨️ 86 ➦ 328

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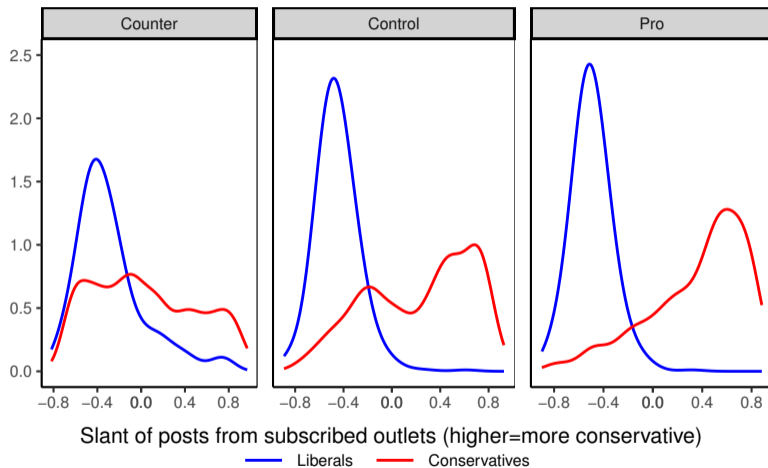
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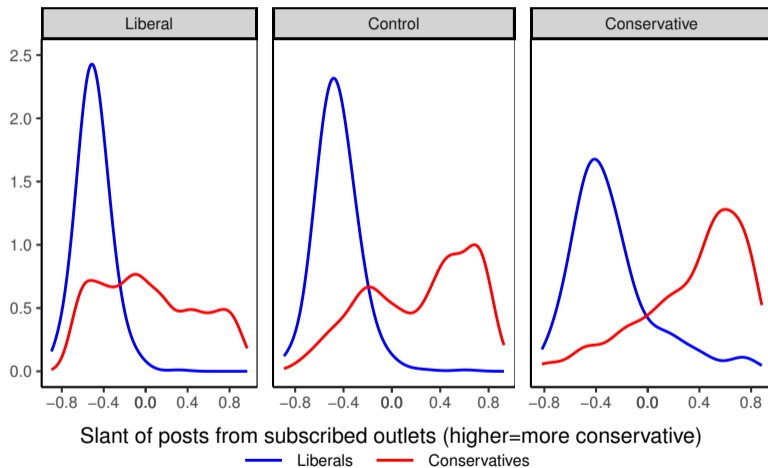
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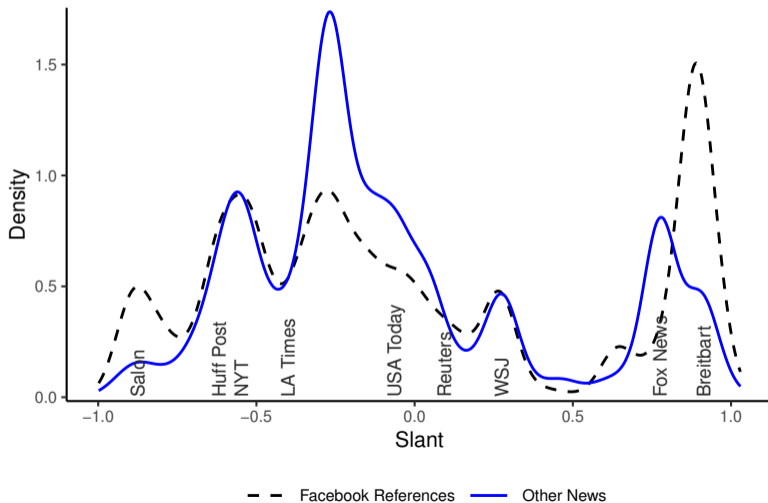
Slant of Outlets in Feed: Pro vs Counter

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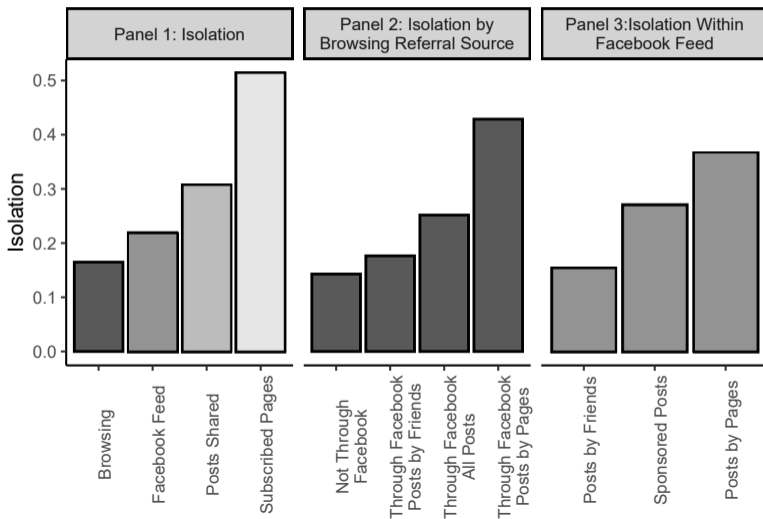
Slant of Outlets in Feed

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Social Media and Extreme News - Site Level

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Outlets' Social Media Links Increase Segregation

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Demand Effects

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- **Subscriptions:** Demand effect likely, similar to other nudges
- **Other outcomes:** Demand effect unlikely. Requires
 - Understand experimenter's expectation
 - Purpose of survey understood similarly in the treatment arms
 - Conscious of experiment
 - Outcome collected separately from intervention
 - No notifications, midline surveys, quizzes
 - Natural intervention, affects less than 5% of posts in the feed
 - Remember intervention in endline
 - Results persist for at least 12 weeks
 - Only ~40% of treated participants stated they remembered if and to which outlet they subscribed (some misunderstood the question or remembered incorrectly, probably upper bound)

Facebook Dominant Social Network

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- Popular

- 71% of US adults. Most visit several times a day
- 79% of 16-64 year old internet users outside China (GlobalWebIndex, 2018)
- 14% of time Americans spend online (Comscore, 2016), 45% of time spent on social media (eMarketer)

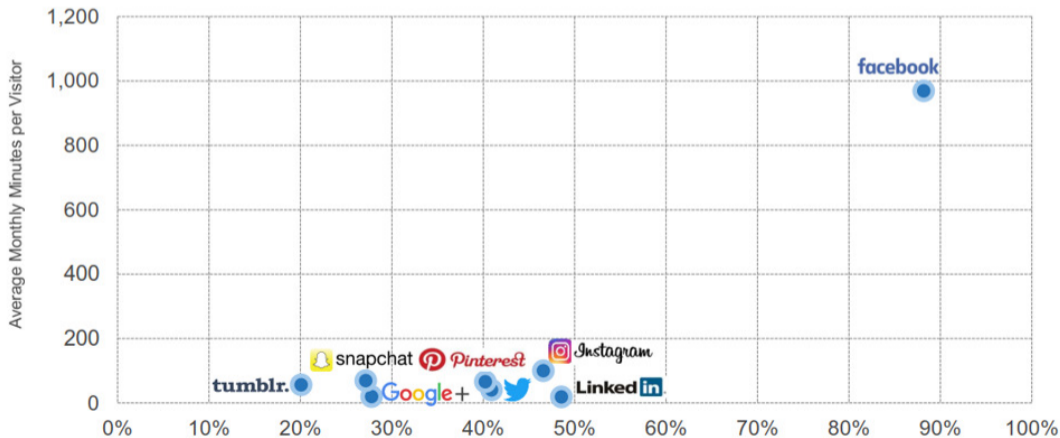
- Major news source

- 23% of 2016 U.S. Presidential candidate coverage (Parse.ly)
- *“Among Millennials, Facebook is far and away the most common source for news about government and politics”* (Pew, 2014)
- In 37 out of 38 middle and high-income countries surveyed, more than 20% consumed news through Facebook weekly (Reuters Institute, 2019)

Facebook's vs Other Social Networks 35+

Age 35+ Digital Audience Penetration vs. Engagement of Leading Social Networks

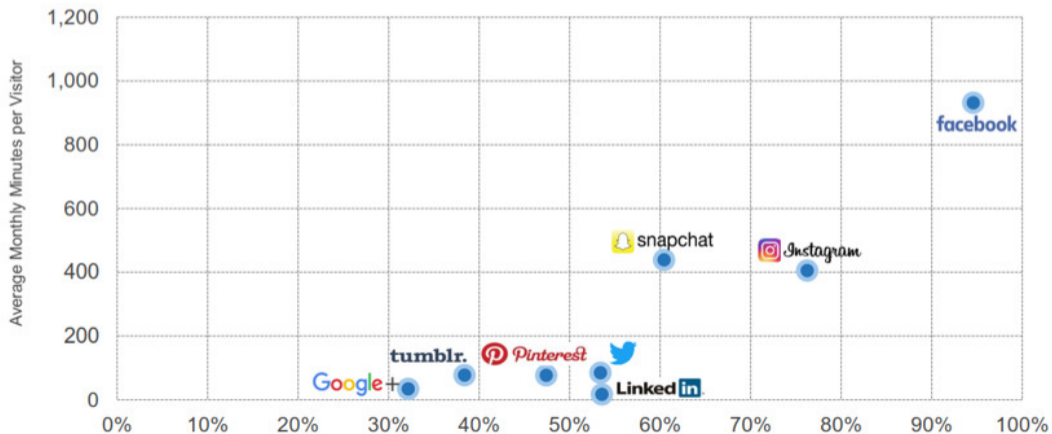
Source: comScore Media Metrix Multi-Platform, U.S., Dec 2016



Facebook's vs Other Social Networks 18-34

Age 18-34 Digital Audience Penetration vs. Engagement of Leading Social Networks

Source: comScore Media Metrix Multi-Platform, U.S., Dec 2016



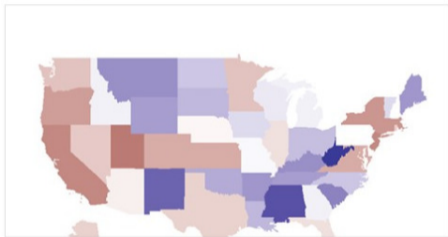
Ad - Opinion

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119 Comments 50 Shares



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Comment



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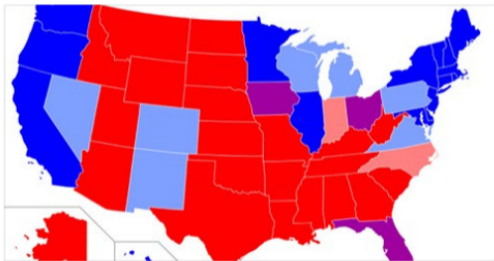


Ad - Politics

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👍👎👤 103

87 Comments 38 Shares



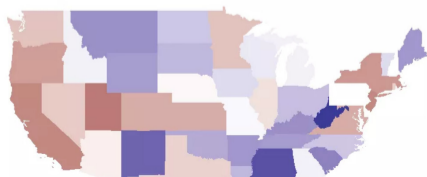
Mobile Ad - Opinion

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Yale Media Survey

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Participate in a short Yale University research survey and you can win an \$80 Amazon gift card



Liberal Treatment Alternative

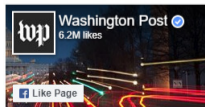
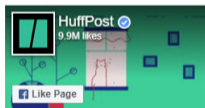
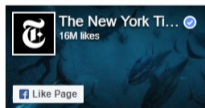
Alternative Outlets

◀ Back

Following a news or media page is a great way to learn about the news and hear other perspectives. Recently, researchers have suggested that subscribing to random sources can help burst the social media echo chamber.

By clicking like below, posts from randomly chosen popular Facebook pages may start appearing in your news feed. **To expand your horizons, please click "Like Page" on 1-4 of the pages below** (Facebook may ask you to confirm the like, you can always unlike the page later).

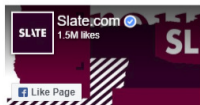
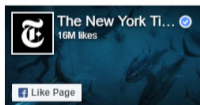
The pages were chosen randomly and therefore may all represent views you agree or disagree with. In any case, they present an opportunity to diversify your news feed.



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Liberal Treatment

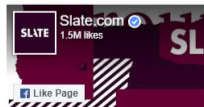
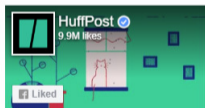
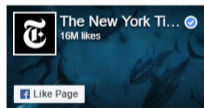
Alternative Outlets

◀ Back

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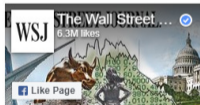
Conservative Treatment

[Alternative Outlets](#)[◀ Back](#)

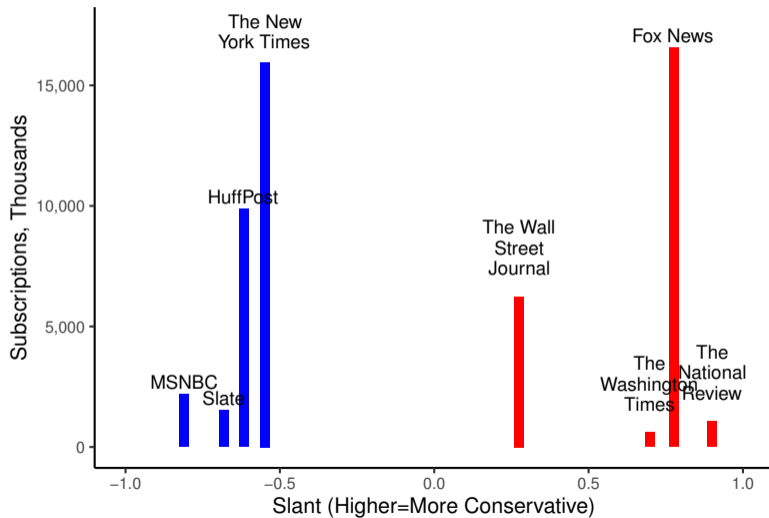
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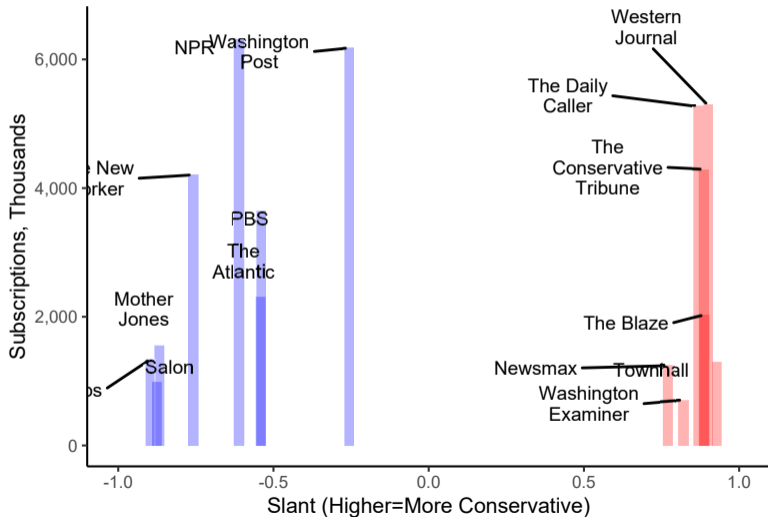
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Outlets

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Alternative Outlets



Facebook suggestion

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Naomi Webber and Arna Yastrow shared Occupy Democrats's post. ...



In 1996, after a gun massacre left 35 dead, Australia **banned** semiautomatic and automatic rifles and shotguns.

What happened? Their gun homicide rate fell by 59% and the gun suicide rate fell by 65%, without a parallel increase in non-firearm homicides and suicides.

Share if we should follow Australia's lead!

OCCUPY DEMOCRATS

Occupy Democrats
October 2 at 10:06am · 🌐

👍 Like Page



ENOUGH IS ENOUGH!



Image by Occupy Democrats, like our page for more.

Facebook suggestion (2)

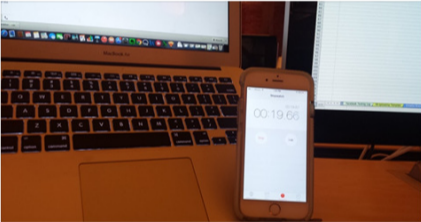
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Suggested Post

 **HubSpot**
Sponsored · 

 Like Page 



Talk about a good time investment:








The CRM That Takes 25 Seconds To Set Up, But Saves Up to 124 Hours Per Year

Discover a brand new sales tool that takes seconds to install, but saves you more time than you can imagine.

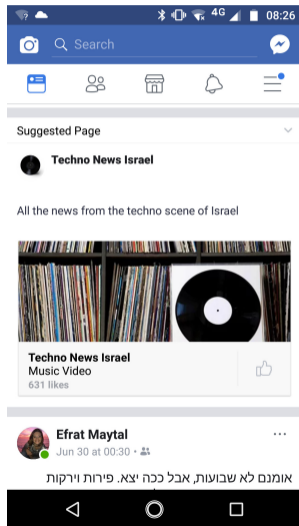
WWW.HUBSPOT.COM/CRM

   20K

2.1K Comments 3.5K Shares  

 Like  Comment  Share

Facebook suggestion (3)

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Survey Data

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- Self-reported political beliefs (N = 17,162)
 - Participants invited through email, Facebook ads, Facebook notification, the browser extension
- Match to baseline survey
 - Invitation, Facebook account, email, unique zip code and name
- Exclude
 - Respondents who are not paying attention (complete too quickly, do not answer many questions, skip last page)
 - Respondents who complete the survey a second time

Facebook Data

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- Log in to the survey using Facebook App
 - Permissions to posts and likes not mandatory, could be revoked at any time, revoked automatically after 2 months
- “Likes” - current pages subscribed to
 - Exclude
 - Participants who do not provide permissions (4.01%)
 - Too many subscriptions (0.85%)
- Posts - content shared with social network (N=34,592)
 - Match with outlet by domain and Facebook page
 - Include only posts shared by the participants
 - Exclude photos, albums, events, music (include links, statuses notes and videos)
 - 227,200 shared posts from leading outlets

Browser Data

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- Chrome extension (N=1,835) [Screenshots](#)
 - Only when logged in to Chrome on a computer
 - 8,084 participants offered, 2,262 installed for small reward
- News exposure: Facebook feed
 - Match with outlet by domain and Facebook page
 - 459,946 posts from leading outlets
- Browsing behavior: news sites visited
 - URLs converted to final redirected URL (e.g. tinyurl.com/... -> huffingtonpost.com/...)
 - Exclude sites
 - Accessed less than a second before visiting same domain
 - Visited twice within 20 minutes
 - 148,327 visits to leading outlets

Install App (1)

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My name is Ro'ee Levy and I am a graduate student from Yale University. I am conducting a research study on media and politics (HSC # 2000021422). Participation in this study involves completing a 5-10 minute survey. You may also be invited to participate in a similar survey in the future.

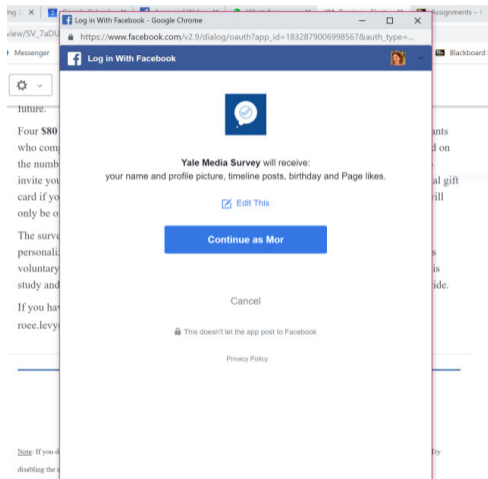
Four **\$80 Amazon gift cards** will be distributed to randomly selected participants. All participants who complete the survey and provide an email address are eligible (the odds of winning depend on the number of participants). You will only be contacted if you won the gift card and possibly to invite you to participate in a future survey. You may be offered an option to receive an additional gift card if you choose to install the survey's chrome extension. This option is not mandatory and will only be offered to some participants.

The survey asks for access to pages liked, posts and birthday from your Facebook profile to personalize some of the questions and to better analyse the results. Providing this information is voluntary. All of your responses will be held in confidence. Only the researchers involved in this study and those responsible for research oversight will have access to the information you provide.

If you have any questions or comments about the study you may contact me by email at roee.levy@yale.edu [Click for additional contact information](#)

 [Log in and begin survey](#)

Install App (2)

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Install Extension (1)

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Yale Qualtrics Survey Tool

Thank you!

To install the extension, click the **Install** button below, and in the pop-up window that opens, click "Add Extension".

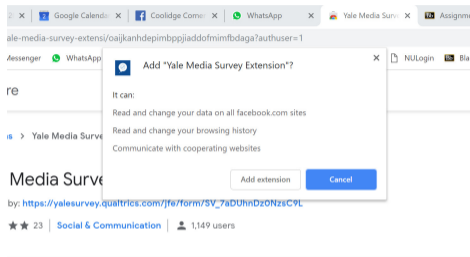
Anyone who completes the survey and has the extension installed for at least two days is eligible for the reward.

A blue rounded rectangular button with the word "Install" in white text.

If you changed your mind for any reason, please click the next button at the bottom of page to complete the final section of the survey (you will still be eligible for the main survey lotteries, but not for the extension rewards).

A dark blue rounded rectangular button with white text ">>".

Install Extension (2)

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Install Extension (3)

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economics.yale.edu

Department of Economics

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A NEW CENTER. A NEW BUILDING.

Tobin Center for Economic Policy

News

[Department Selects 2019-20 Peer Mentors](#)

The Department has selected rising seniors Devesh Agrawal, Jingyi Cui, and rising junior Lara Varela Gajewski as its Economics and Economics & Mathematics mentors for the...

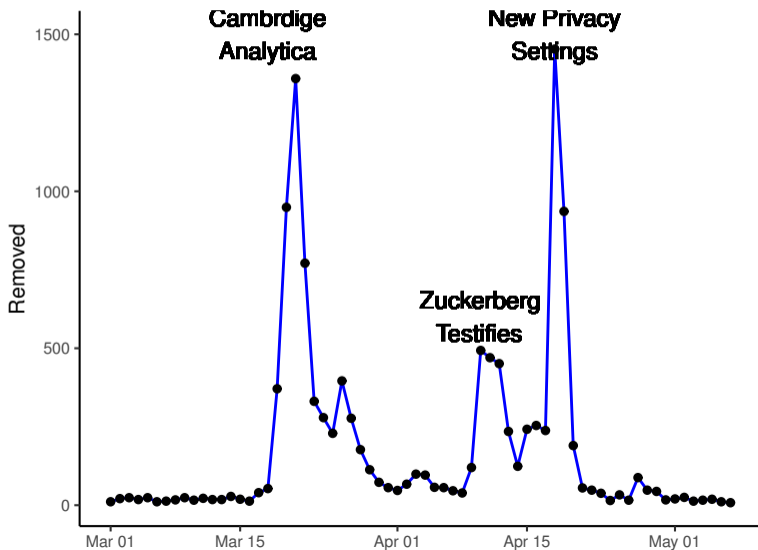
MORE NEWS...

Upcoming Featured Events

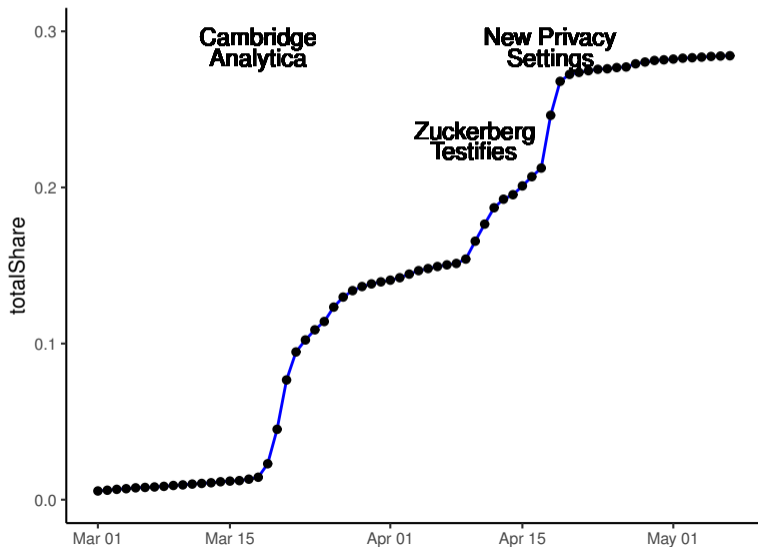
AUGUST 26

Departmental Event

Removed App

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Removed App - CDF

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Compliers

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		Control	All Comply:		Pro-Att. Comply:		Counter-Att. Comply:		Liberal Comply:		Conservative Comply:	
			Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
1)	Ideology (-3, 3)	-0.62	-0.92	-0.27	-0.86	-0.31	-1.05	-0.25	-1.13	-0.04	-0.71	-0.51
2)	Ideology, Abs. Value (0, 3)	1.80	1.77	1.73	1.83	1.75	1.78	1.82	1.78	1.72	1.75	1.75
3)	Democrat	0.40	0.43	0.32	0.44	0.32	0.46	0.34	0.47	0.27	0.40	0.37
4)	Republican	0.17	0.13	0.21	0.15	0.21	0.12	0.23	0.11	0.25	0.16	0.18
5)	Independent	0.35	0.36	0.37	0.35	0.38	0.36	0.35	0.35	0.38	0.37	0.36
6)	Vote Support Clinton	0.54	0.60	0.44	0.60	0.46	0.64	0.46	0.65	0.39	0.55	0.50
7)	Vote Support Trump	0.27	0.20	0.34	0.23	0.34	0.17	0.36	0.15	0.38	0.25	0.29
8)	Feeling Therm., Difference	50.47	50.24	49.92	51.23	48.52	49.03	51.02	50.70	49.33	49.79	50.51
9)	Difficult Pers., Difference	1.93	1.93	1.88	1.97	1.81	1.89	1.95	1.94	1.89	1.92	1.88
10)	Facebook Echo Chamber	1.20	1.21	1.15	1.23	1.14	1.22	1.19	1.23	1.13	1.19	1.17
11)	Most News Social Media	0.17	0.18	0.17	0.17	0.17	0.19	0.17	0.18	0.17	0.17	0.17
12)	Took Survey Mobile	0.67	0.67	0.67	0.67	0.68	0.68	0.66	0.69	0.67	0.66	0.67
13)	Female	0.52	0.57	0.46	0.56	0.47	0.60	0.45	0.59	0.45	0.56	0.47
14)	Age	47.94	48.32	46.95	49.03	46.32	47.86	47.86	48.18	46.74	48.46	47.16
15)	Total Subscriptions	476	509	430	496	431	521	429	515	428	504	431
16)	News Outlets Subscriptions	8.16	8.77	7.41	8.87	7.26	8.79	7.73	8.78	7.40	8.75	7.42
17)	Certain (0, 4)	3.16	3.12	3.18	3.14	3.17	3.11	3.20	3.11	3.17	3.13	3.19
18)	Open Personality (1, 7)	5.62	5.70	5.54	5.67	5.55	5.72	5.52	5.71	5.53	5.68	5.55

Compliance, Outlet Level Regression

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	(1)	(2)
Cons. Treat., Cons. Ideology	0.513*** (0.008)	
Lib. Treat., Cons. Ideology	0.349*** (0.008)	
Cons. Treat., Lib. Ideology	0.541*** (0.006)	
Lib. Treat., Lib. Ideology	0.623*** (0.006)	
Know Slant		0.230*** (0.006)
Outlet Ideology, Abs. Value (Std. Dev.)		-0.047*** (0.003)
Ideological Distance (Std. Dev.)		-0.083*** (0.002)
Controls	X	X
Observation Unit	Ind.	Ind. * Outlet Offered
Observations	36,728	97,937

Descriptive Statistics by Subsample

	Baseline Sample	Access Posts Subsample	Endline Survey Subsample	Extension Subsample
1) Ideology (-3, 3)	-0.61	-0.61	-0.71	-0.95
2) Ideology, Abs. Value (0, 3)	1.75	1.75	1.80	1.81
3) Democrat	0.38	0.38	0.40	0.44
4) Republican	0.17	0.17	0.16	0.14
5) Independent	0.37	0.36	0.36	0.36
6) Feeling Therm., Difference	50.22	50.27	50.32	51.08
7) Difficult Pers., Difference	1.92	1.92	1.96	1.92
8) Most News Social Media	0.18	0.18	0.17	0.16
9) Took Survey Mobile	0.67	0.67	0.63	0.00
10) Female	0.52	0.52	0.52	0.49
11) Age	47.69	47.65	48.78	52.47
12) Total Subscriptions	474	474	472	481
13) News Outlets Subscriptions	8.11	8.11	8.28	8.61
14) Compliance	0.53	0.53	0.58	0.76
15) N	37,494	34,592	17,635	1,835

Baseline Balance - Pro. vs Counter

Variable	Mean		Difference		
	Sample N=36,330	US	Control - Pro.	Control - Counter.	Pro. - Counter.
Baseline Survey					
Ideology, Abs. Value (0, 3)	1.80	1.31	0.00	-0.00	-0.00
Democrat	0.39	0.37	0.01	0.00	-0.01
Republican	0.17	0.30	0.00	-0.01	-0.01
Independent	0.36	0.29	-0.01*	0.00	0.01**
Vote Support Clinton	0.54		-0.00	-0.00	0.00
Vote Support Trump	0.27		0.00	0.00	0.00
Feeling Therm., Difference	50.22	38.44	0.36	0.41	0.05
Difficult Pers., Difference	1.92		0.03	0.02	-0.02
Facebook Echo Chamber	1.20		0.00	-0.01	-0.01
Follows News	3.36	2.48	0.01	0.01	0.01
Most News Social Media	0.17	0.12	0.00	-0.00	-0.01
Device					
Took Survey Mobile	0.67		-0.01*	-0.00	0.01*
Facebook					
Female	0.52	0.52	-0.01	-0.00	0.00
Age	47.91	47.70	0.02	0.08	0.06
Total Subscriptions	473		6.91	3.16	-3.75
News Outlets Slant, Abs. Value	0.54		-0.00	-0.00	0.00
Access Posts, Pre-Treat.	0.98		0.00	0.00	-0.00
Attrition					
Took Followup Survey	0.47		0.03***	0.03***	0.00
Access Posts, 2 Weeks	0.92		0.01	0.00	-0.00
Extension Install, 2 Weeks	0.05		0.00	-0.00	-0.00
F-Test			1.23	0.80	0.99
P-value			[0.20]	[0.75]	[0.48]

Baseline Balance - Liberal vs Conservative

Variable	Mean			Difference		
	Sample N=37,494	US	FB Users	Control - Lib.	Control - Cons.	Cons. - Lib.
Baseline Survey						
Ideology (-3, 3)	-0.61	0.17		0.01	0.01	0.00
Democrat	0.38	0.35	0.30	0.01	0.00	0.01
Republican	0.17	0.28	0.21	-0.01	0.00	-0.01
Independent	0.37	0.32	0.35	-0.00	-0.00	-0.00
Vote Support Clinton	0.53			-0.00	-0.00	-0.00
Vote Support Trump	0.26			0.00	-0.00	0.01
Feeling Therm., Rep.	29.07	43.06		0.11	0.25	-0.13
Feeling Therm., Dem.	46.99	48.70		0.40	0.46	-0.06
Difficult Pers., Rep. (1, 5)	3.13			0.02	0.00	0.02
Difficult Pers., Dem. (1, 5)	2.39			-0.00	0.01	-0.01
Facebook Echo Chamber	1.18		1.12	-0.00	-0.00	0.00
Follows News	3.35	2.42		0.01	0.01	-0.00
Most News Social Media	0.18	0.13		-0.00	0.00	-0.00
Device						
Took Survey Mobile	0.67			-0.01*	-0.00	-0.01*
Facebook						
Female	0.52	0.52	0.55	-0.01	-0.00	-0.00
Age	47.69	47.30	42.86	0.22	-0.13	0.35
Total Subscriptions	474			5.15	9.04	-3.89
News Outlets Slant (-1, 1)	-0.18			0.00	0.00	0.00
Access Posts, Pre-Treat.	0.98			0.00	0.01***	-0.00**
Attrition						
Took Followup Survey	0.47			0.03***	0.03***	-0.00
Access Posts, 2 Weeks	0.92			0.00	0.01**	-0.01**
Extension Install, 2 Weeks	0.05			0.00	-0.00	0.00
F-Test				1.20	0.89	1.05
P-Value				[0.21]	[0.64]	[0.39]

Followup Balance - Pro vs. Counter

Variable	Mean		Difference		
	Sample N=17,130	US	Control - Pro.	Control - Counter.	Pro. - Counter.
Baseline Survey					
Ideology, Abs. Value (0, 3)	1.84	1.31	-0.00	0.00	0.00
Democrat	0.41	0.37	0.02*	0.01	-0.01
Republican	0.16	0.30	0.00	0.00	-0.00
Independent	0.35	0.29	-0.02**	-0.00	0.01
Vote Support Clinton	0.57		-0.00	0.00	0.00
Vote Support Trump	0.25		0.00	0.01	0.01
Feeling Therm., Difference	50.32	38.44	0.96*	1.10**	0.14
Difficult Pers., Difference	1.96		0.05*	0.04	-0.01
Facebook Echo Chamber	1.22		0.00	0.00	-0.00
Follows News	3.39	2.48	0.02	0.03*	0.00
Most News Social Media	0.17	0.12	-0.00	-0.01	-0.00
Device					
Took Survey Mobile	0.63		-0.01	0.01	0.01
Facebook					
Female	0.52	0.52	-0.01	-0.01	0.00
Age	48.96	47.70	0.12	0.20	0.08
Total Subscriptions	471		4.99	3.30	-1.69
News Outlets Slant, Abs. Value	0.55		-0.00	0.00	0.00
Access Posts, Pre-Treat.	0.98		-0.00	0.00	0.00
F-Test			0.63	0.75	0.57
P-value			[0.89]	[0.78]	[0.94]

Followup Balance - Liberal vs. Conservative

Variable	Mean			Difference		
	Sample N=17,635	US	FB Users	Control - Lib.	Control - Cons.	Cons. - Lib.
Baseline Survey						
Ideology (-3, 3)	-0.71	0.17		-0.01	-0.02	0.01
Democrat	0.40	0.35	0.30	0.01	0.01	0.01
Republican	0.16	0.28	0.21	0.00	0.00	0.00
Independent	0.36	0.32	0.35	-0.02*	-0.01	-0.01
Vote Support Clinton	0.55			-0.00	-0.00	-0.00
Vote Support Trump	0.25			0.01	-0.00	0.01
Feeling Therm., Rep.	27.54	43.06		0.20	-0.04	0.24
Feeling Therm., Dem.	47.79	48.70		0.43	0.68	-0.25
Difficult Pers., Rep. (1, 5)	3.18			0.04	0.01	0.04
Difficult Pers., Dem. (1, 5)	2.35			-0.01	-0.03	0.03
Facebook Echo Chamber	1.20		1.12	0.01	-0.01	0.01
Follows News	3.38	2.42		0.02	0.02	-0.00
Most News Social Media	0.17	0.13		-0.01**	-0.00	-0.01*
Device						
Took Survey Mobile	0.63			-0.01	0.01	-0.01
Facebook						
Female	0.52	0.52	0.55	-0.01	-0.00	-0.00
Age	48.78	47.30	42.86	0.55*	-0.31	0.86**
Total Subscriptions	472			2.37	15.27	-12.90
News Outlets Slant (-1, 1)	-0.20			0.00	-0.01	0.01
Access Posts, Pre-Treat.	0.98			0.00	0.00*	-0.00
F-Test				1.15	0.97	1.32
P-Value				[0.29]	[0.49]	[0.16]

Specification - Media Regressions

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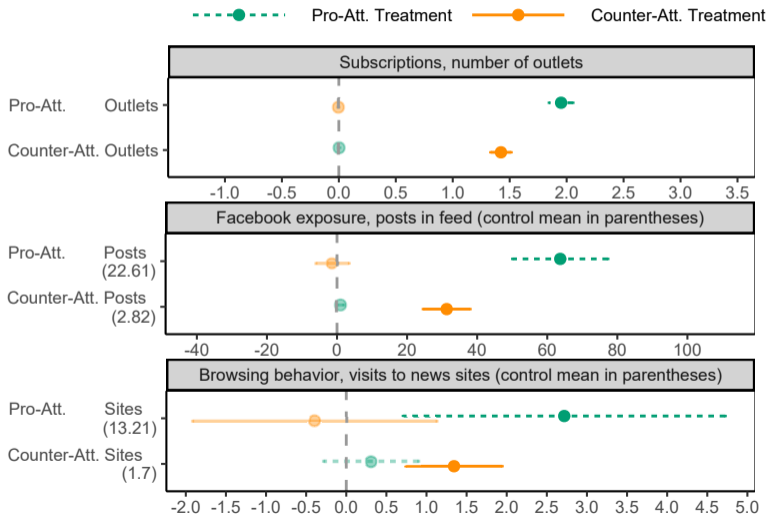
Liberal vs Conservative

- $Y_i = \beta_1 T_i^L + \beta_2 T_i^C + \alpha X_i + \varepsilon_i$ where
 - T_i^L is whether participant i assigned to the liberal treatment
 - T_i^C is whether participant i assigned to the conservative treatment
 - X is the outcome variable in the pre-period (if observed)

Pro vs. Counter

- $Y_i = \beta_1 T_i^P + \beta_2 T_i^A + \alpha X_i + \varepsilon_i$
 - T_i^P is whether participant i assigned to the pro-att. treatment
 - T_i^A is whether participant i assigned to the counter-att. treatment

ITT After Two Weeks: Pro vs. Counter Attitudinal



Participants in Post Sharing and Extension Subsamples (N=1,648)

ITT Regression: Pro vs. Counter Attitudinal

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	Pro-Att. Outlets New Subscriptions	Pro-Att. Outlets Facebook Exposure	Pro-Att. Outlets Browsing Behavior	Pro-Att. Outlets Sharing Behavior	Counter-Att. Outlets New Subscriptions	Counter-Att. Outlets Facebook Exposure	Counter-Att. Outlets Browsing Behavior	Counter-Att. Outlets Sharing Behavior
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pro-Att. Treatment	1.95*** (0.06)	63.71*** (8.29)	2.72** (1.22)	0.42*** (0.14)	0.01 (0.004)	1.09* (0.56)	0.31 (0.36)	0.01 (0.02)
Counter-Att. Treatment	-0.0001 (0.004)	-1.36 (2.80)	-0.40 (0.92)	0.03 (0.11)	1.42*** (0.06)	31.30*** (4.09)	1.34*** (0.37)	0.18*** (0.05)
Pro Treat - Counter Treat	1.95*** (0.06)	65.07*** (8.21)	3.11*** (1.17)	0.39*** (0.13)	-1.42*** (0.06)	-30.21*** (4.11)	-1.04*** (0.40)	-0.17*** (0.05)
Control Mean	0	22.61	13.21	0.84	0	2.82	1.7	0.11
Observations	1,648	1,648	1,648	1,648	1,648	1,648	1,648	1,648

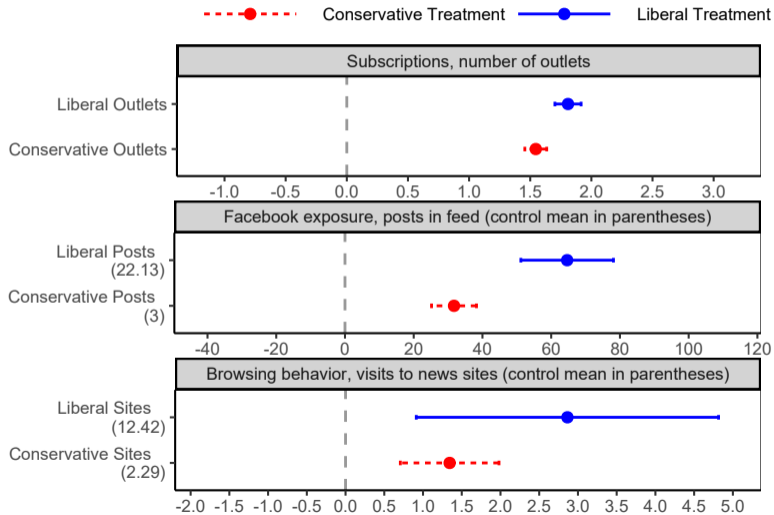
[Poisson](#)[Treat. * Ideolgy](#)

Pro vs. Counter Attitudinal - Poisson

[◀ Back](#)

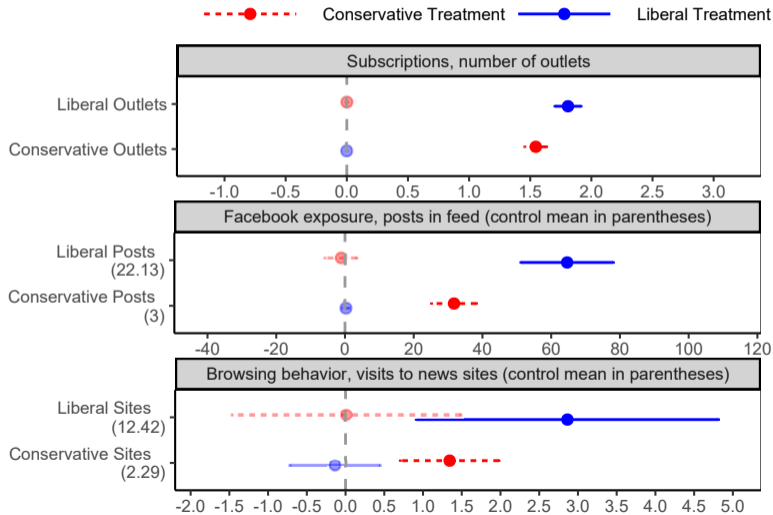
	Pro-Att. Outlets Facebook Exposure (1)	Pro-Att. Outlets Browsing Behavior (2)	Pro-Att. Outlets Sharing Behavior (3)	Counter-Att. Outlets Facebook Exposure (4)	Counter-Att. Outlets Browsing Behavior (5)	Counter-Att. Outlets Sharing Behavior (6)
Pro-Att. Treat.	1.34*** (0.13)	0.29** (0.14)	0.57*** (0.21)	0.33** (0.16)	0.19 (0.25)	0.17 (0.31)
Counter-Att. Treat.	-0.06 (0.13)	-0.03 (0.14)	0.26 (0.21)	2.49*** (0.16)	0.54*** (0.19)	1.27*** (0.31)
Pro-Att. exponentiated	3.82	1.33	1.77	1.39	1.22	1.18
Counter-Att. exponentiated	0.94	0.97	1.3	12.11	1.72	3.56
Observations	1,648	1,648	1,648	1,648	1,648	1,648

ITT: Liberal vs. Conservative



Participants in FB and Subsamples (N 1,699)

ITT: Liberal vs. Conservative



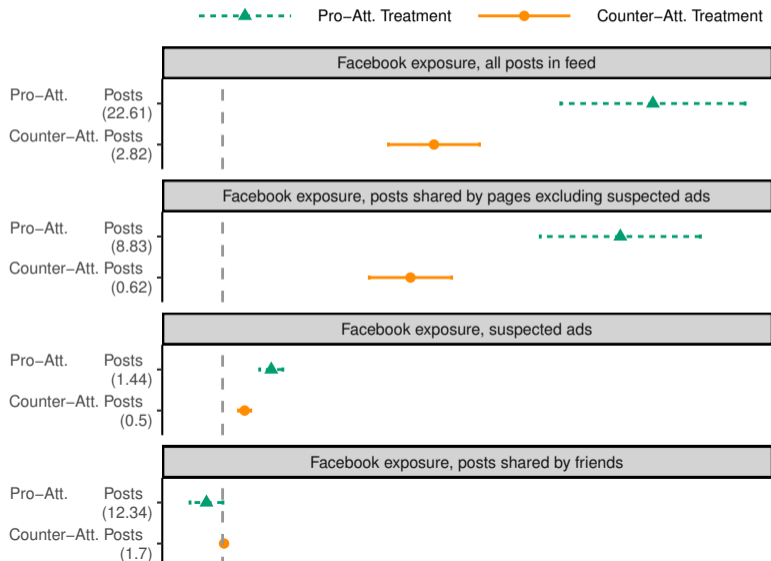
Participants in FB and Subsamples (N 1,699)

ITT Regression: Liberal vs. Conservative

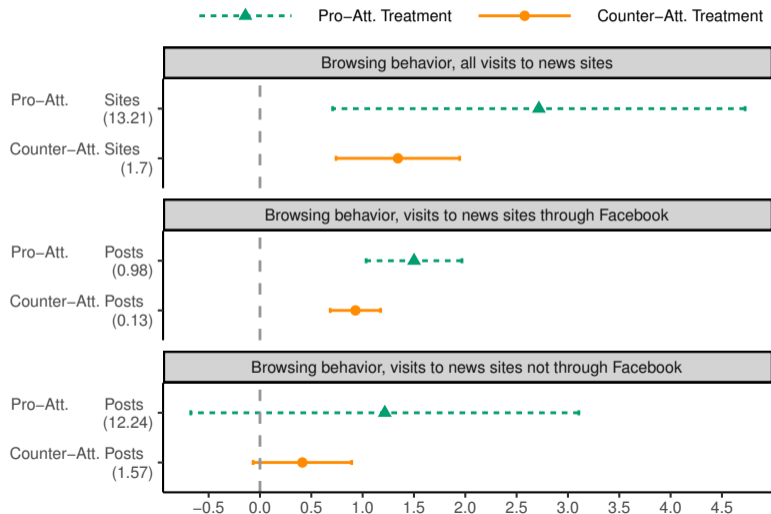
[◀ Back](#)

	Liberal Outlets New Subscriptions	Liberal Outlets Facebook Exposure	Liberal Outlets Browsing Behavior	Liberal Outlets Sharing Behavior	Conservative Outlets New Subscriptions	Conservative Outlets Facebook Exposure
	(1)	(2)	(3)	(4)	(5)	(6)
Liberal Treatment	1.81*** (0.07)	64.65*** (8.18)	2.86** (1.19)	0.002 (0.002)	0.39 (0.51)	-0.14 (0.35)
Conservative Treatment	0.003 (0.005)	-1.10 (2.73)	0.01 (0.89)	1.55*** (0.05)	31.73*** (3.97)	1.34*** (0.39)
Conservative Treat - Liberal Treat	-1.81*** (0.07)	-65.74*** (8.10)	-2.85** (1.13)	1.54*** (0.05)	31.34*** (3.99)	1.48*** (0.39)
Control Mean	0.004	22.131	12.417	0	3.002	2.292
Observations	1,699	1,699	1,699	1,699	1,699	1,699

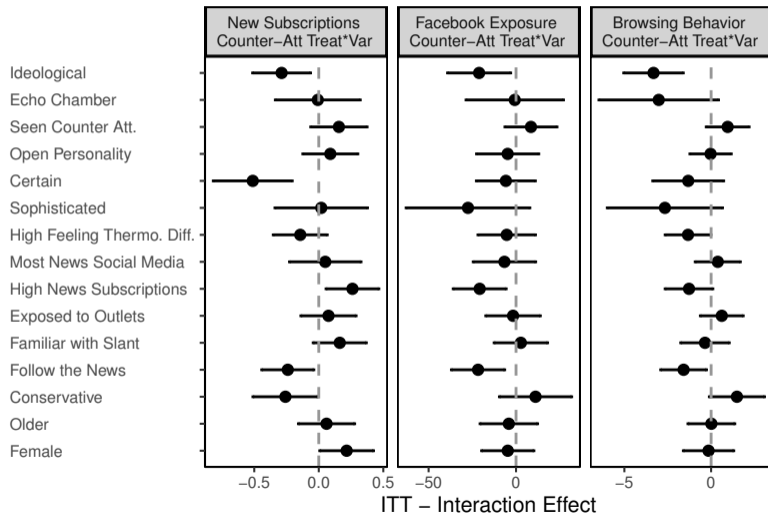
ITT: Exposure by Post Type

[◀ Back](#)


ITT: Browsing Referral Source

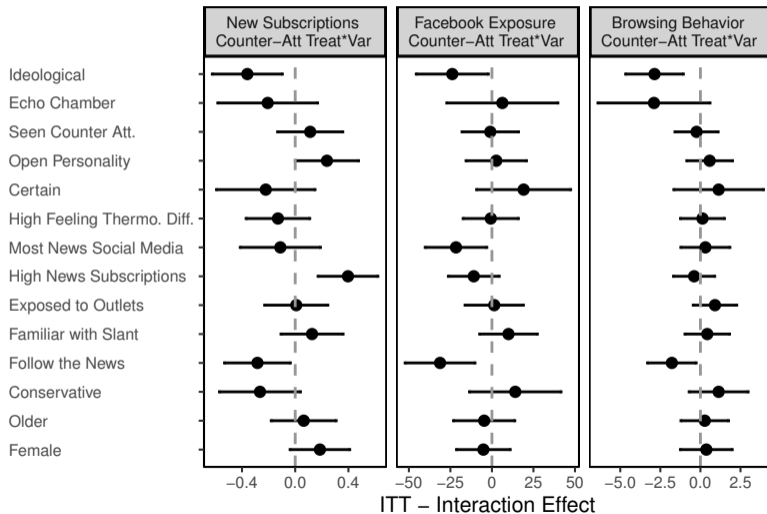


Hetero. Effect of Counter-Att. on Counter-Att. Outlets



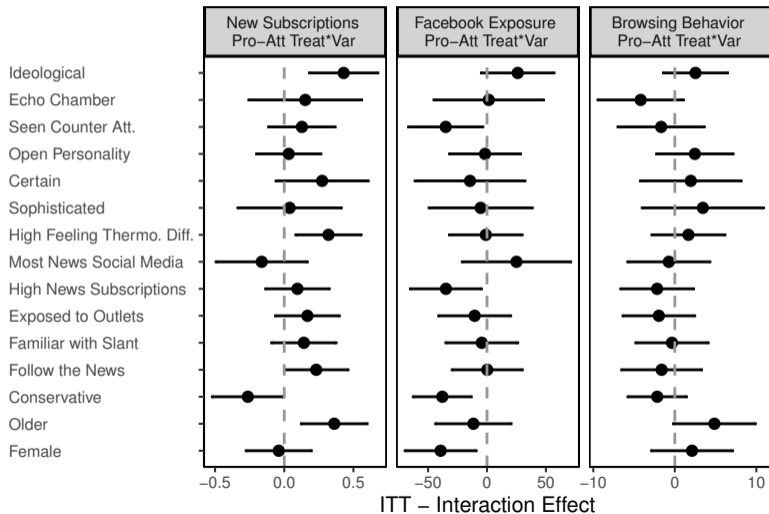
Effect of interacting each binary covariate with the treatment on engagement with counter-attitudinal outlets.

Hetero. Effect of Counter-Att. on Counter-Att. Outlets



Effect of interacting the covariates with treatment on engagement with counter-attitudinal outlets (joint regression).

Hetero. Effect of Pro-Att. on Pro-Att. Outlets



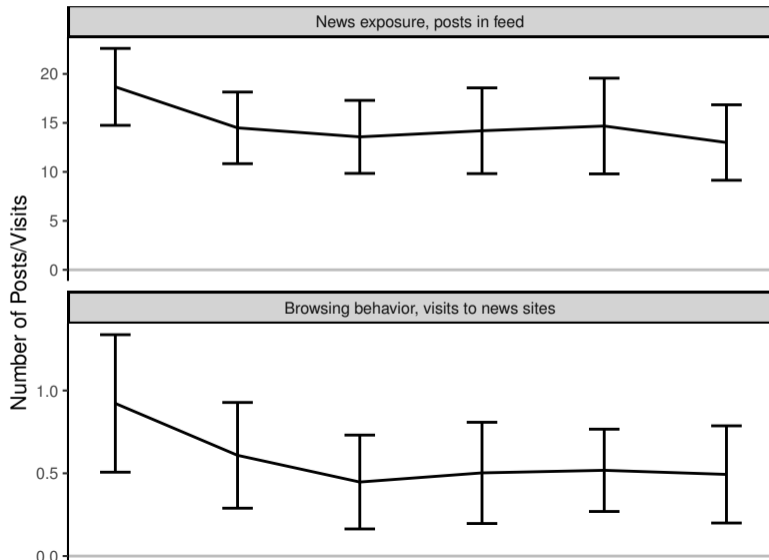
Effect of interacting each binary covariate with the treatment on engagement with pro-attitudinal outlets.

Media Behavior Summary By Subgroup

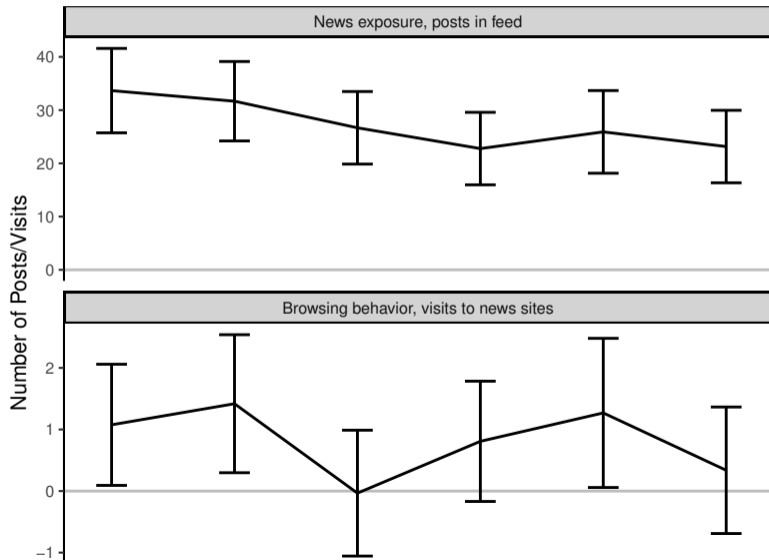
[◀ Back](#)

	Liberal Outlets New Subscriptions	Liberal Outlets Facebook Exposure	Liberal Outlets Browsing Behavior	Conservative Outlets New Subscriptions	Conservative Outlets Facebook Exposure	Conservative Outlets Browsing Behavior
	(1)	(2)	(3)	(4)	(5)	(6)
Lib. Treat., Lib. Ideology	2.04*** (0.08)	72.71*** (10.73)	2.99* (1.66)	0.003 (0.003)	0.12 (0.28)	-0.05 (0.40)
Lib. Treat., Cons. Ideology	1.23*** (0.12)	37.07*** (10.59)	1.95** (0.87)	0.00** (0.00)	1.01 (1.74)	-0.21 (0.82)
Cons. Treat., Lib. Ideology	-0.0004 (0.005)	-3.39 (3.71)	-0.56 (1.22)	1.49*** (0.06)	29.54*** (4.18)	1.19*** (0.40)
Cons. Treat., Cons. Ideology	0.01 (0.01)	3.54** (1.77)	1.03 (0.82)	1.74*** (0.12)	40.81*** (10.26)	1.90* (0.99)
Observations	1,658	1,658	1,658	1,658	1,658	1,658

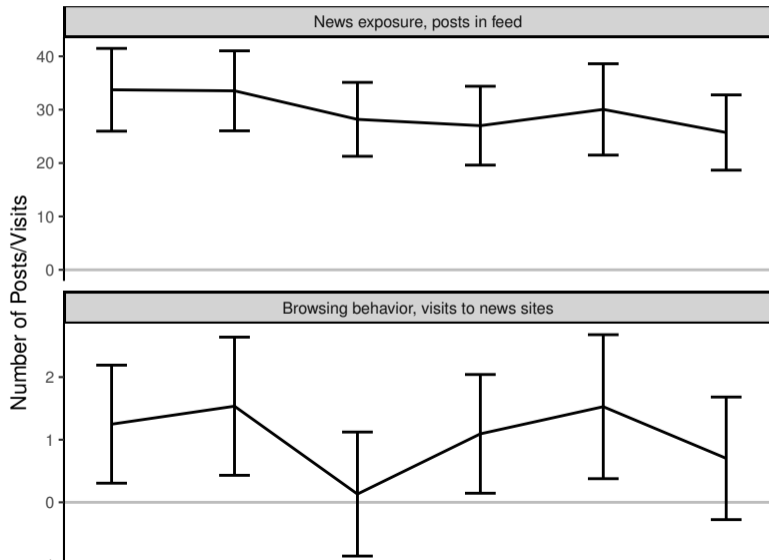
Effects by Week - Counter-Attitudinal

[◀ Back](#)

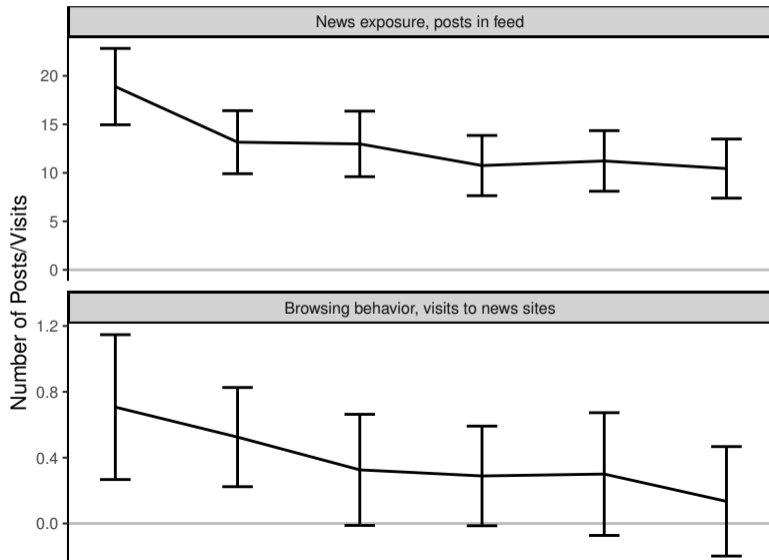
Effects by Week - Pro-Attitudinal

[◀ Back](#)

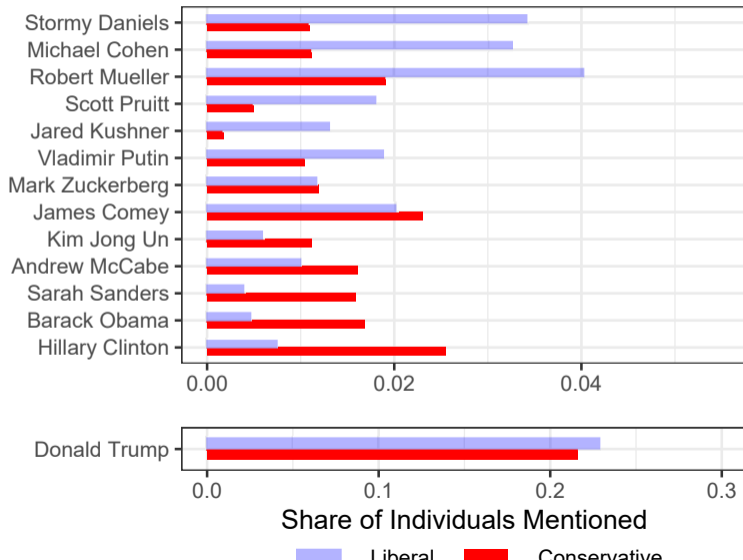
Effects by Week - Liberal

[◀ Back](#)

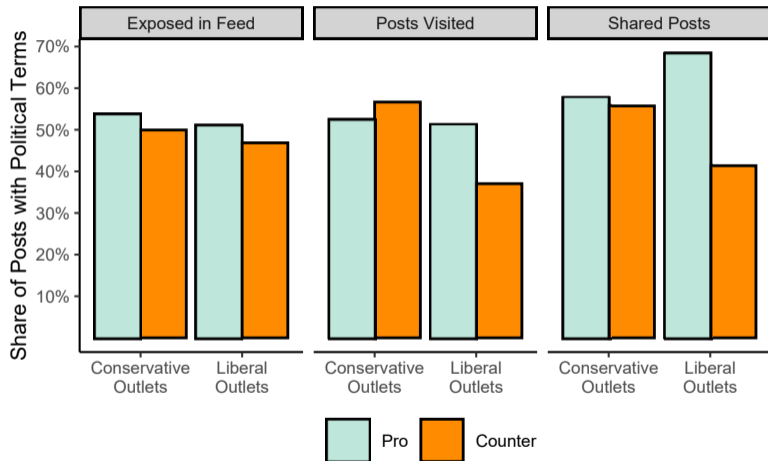
Effects by Week - Conservative

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Primary Outlet Content

[◀ Back](#)


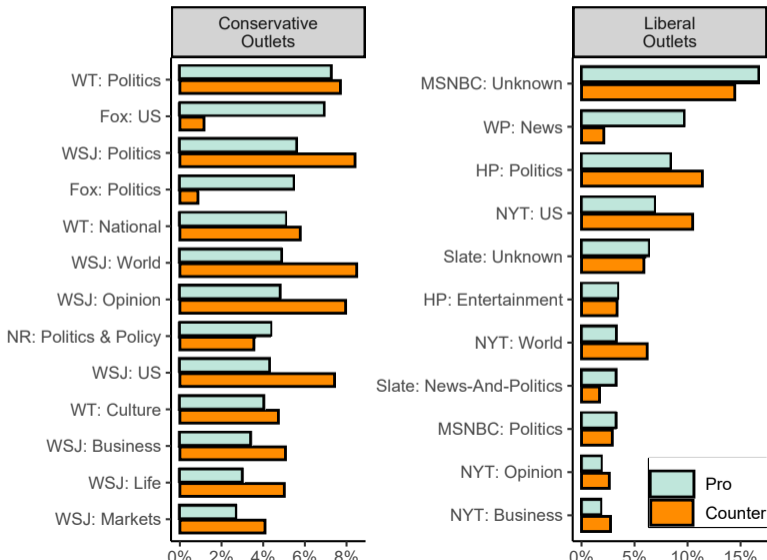
Political Content

[◀ Back](#)


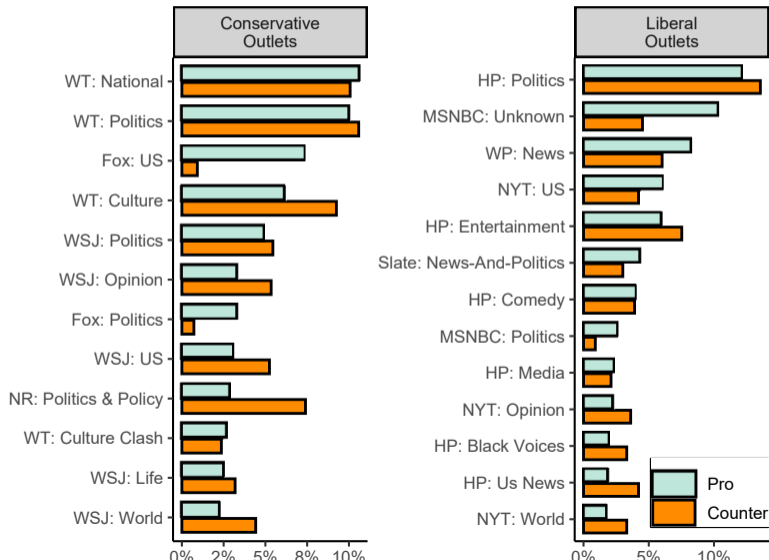
Source: Data from all posts shared by pages participants subscribed to in the 6 weeks following the intervention.

Post is political if contains the following terms: "liberal, conservative, democrat, republican, dnc, gop, the left, the right, trump, pence, pelosi, clinton, obama, biden, mcconnell, manafort, kushner, tillerson, devos, mccabe, elect, vote, white house, politic, congress, senate, immigration, daca, tax cut, sanctuary city/state, school shooting, parkland, nra, gun, mass shooting, gun control, walkout, ar-15"

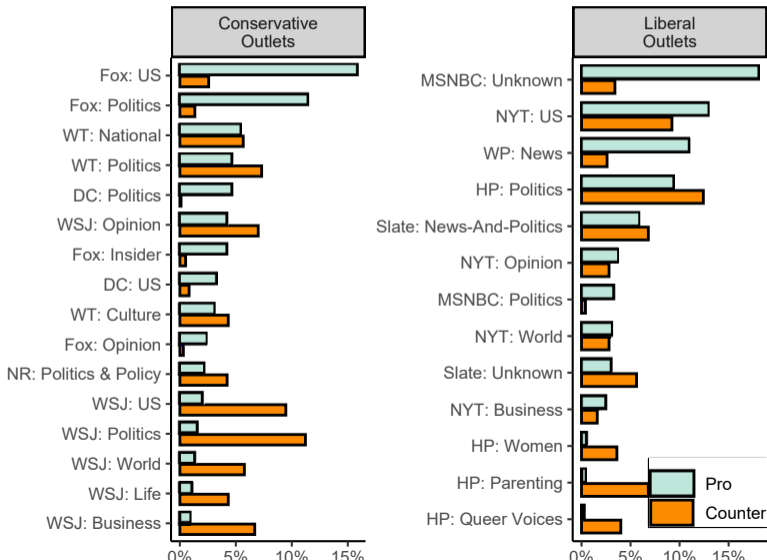
Outlets and Sections, Posts in Feed

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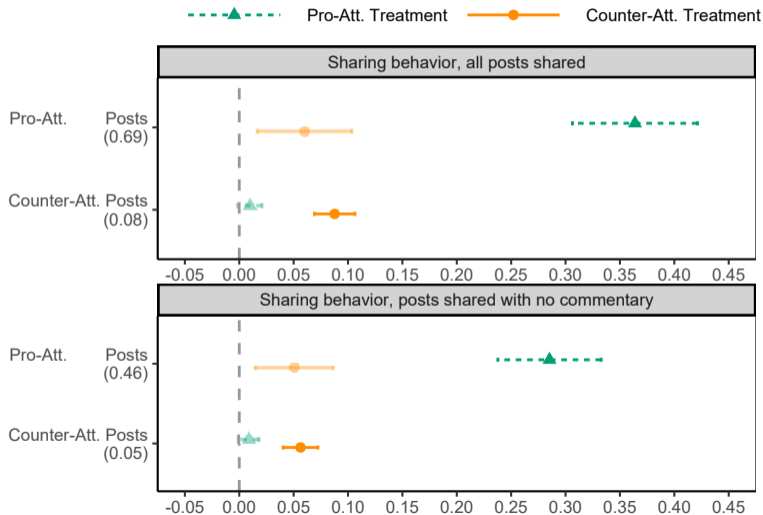
Outlets and Sections, Posts Clicked

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Outlets and Sections, Posts Shared

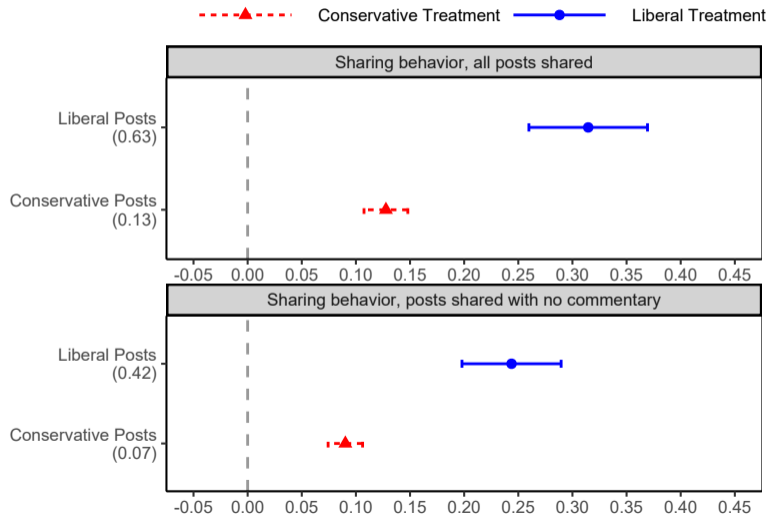
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Engagement with Posts



Participants in Post Sharing Subsample (N=33,532)

Engagement with Posts



Participants in Post Sharing Subsample (N=34,592)

Shared Posts

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	Pro-Att. Outlets Shared	Pro-Att. Outlets Shared No Commentary	Counter-Att. Outlets Shared	Counter-Att. Outlets Shared No Commentary
	(1)	(2)	(3)	(4)
Pro-Att. Treatment	0.36*** (0.03)	0.29*** (0.03)	0.01 (0.01)	0.01* (0.01)
Counter-Att. Treatment	0.06** (0.03)	0.05** (0.02)	0.09*** (0.01)	0.06*** (0.01)
Pro Treat - Counter Treat	-0.08*** (0.01)	-0.05*** (0.01)	0.30*** (0.04)	0.23*** (0.03)
Control Mean	0.084	0.049	0.687	0.457
Observations	33 532	33 532	33 532	33 532

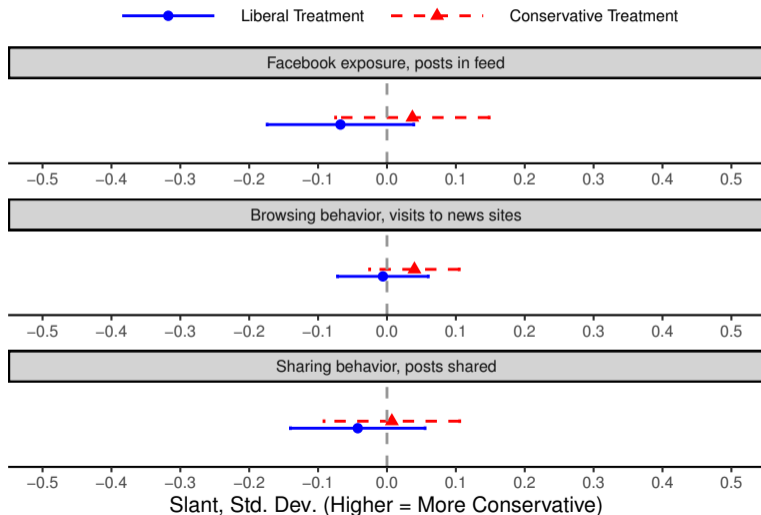
Mean Slant, All Outlets

	News Exposure (1)	Browsing Behavior (2)	Shared Posts (3)	Shared Posts (4)
Conservative Treatment	0.37*** (0.07)	0.11** (0.04)	0.05 (0.06)	0.05*** (0.01)
Liberal Treatment	-0.23*** (0.06)	-0.08** (0.04)	-0.11* (0.06)	-0.02* (0.01)
Cons. Treat. - Lib. Treat.	0.08*** (0.02)	0.16* (0.09)	0.79*** (0.09)	0.19*** (0.07)
TOT: Cons. - Lib. Treatment	0.14	0.2	1.02	0.25
Control: Cons. Ideo. - Lib. Ideo.	1.48	1.51	1.67	1.29 ^{A.79}

Mean Slant, Excluding Experiment Outlets

	News Exposure (1)	Browsing Behavior (2)	Shared Posts (3)	Shared Posts (4)
Conservative Treatment	0.04 (0.07)	0.04 (0.04)	0.01 (0.06)	-0.002 (0.01)
Liberal Treatment	-0.07 (0.06)	-0.01 (0.04)	-0.04 (0.06)	0.003 (0.01)
Cons. Treat. - Lib. Treat.	-0.01 (0.01)	0.05 (0.06)	0.10 (0.07)	0.05 (0.04)
TOT: Cons. - Lib. Treatment	-0.01	0.06	0.13	0.06
Control: Cons. Ideo, - Lib. Ideo.	1.45	1.49	1.6	1.25 ^{A.80}

Slant - Excluding Experiment Outlets

[◀ Back](#)Participants in Post Sharing and Extension Subsamples ($N \leq 1,699$)

Effect on Slant, By Subsample

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	News Exposure			Browsing Behavior			Shared Posts		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Liberal Treatment	-0.237*** (0.060)	-0.234*** (0.063)	-0.191*** (0.073)	-0.091** (0.037)	-0.080** (0.039)	-0.100** (0.046)	-0.021* (0.012)	-0.106* (0.056)	-0.045 (0.065)
Conservative Treatment	0.355*** (0.067)	0.365*** (0.070)	0.462*** (0.082)	0.102** (0.040)	0.105** (0.041)	0.107** (0.050)	0.046*** (0.013)	0.054 (0.060)	0.131* (0.073)
Cons. Treat. - Lib. Treat.	0.59*** (0.06)	0.60*** (0.07)	0.65*** (0.08)	0.19*** (0.04)	0.19*** (0.04)	0.21*** (0.05)	0.07*** (0.01)	0.16*** (0.06)	0.18** (0.07)
Ext. Subsample	X			X					
Posts Subsample							X		
Ext. + Posts Subsample		X			X			X	
Ext. + Posts + Endline Subsample			X			X			X
Observations	1,556	1,433	1,010	1,785	1,652	1,166	18,328	979	685

Effect on Feed Slant, Article-Level

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	Mean Slant (std. dev.)	
	(1)	(2)
Liberal Treatment	-0.461*** (0.101)	-0.133** (0.054)
Conservative Treatment	0.832*** (0.109)	0.122** (0.059)
Conservative Treat - Liberal Treat	1.29*** (0.06)	0.26*** (0.05)
Data = Potential Outlets	X	
Data = All Domains		X
Observations	837	1,805

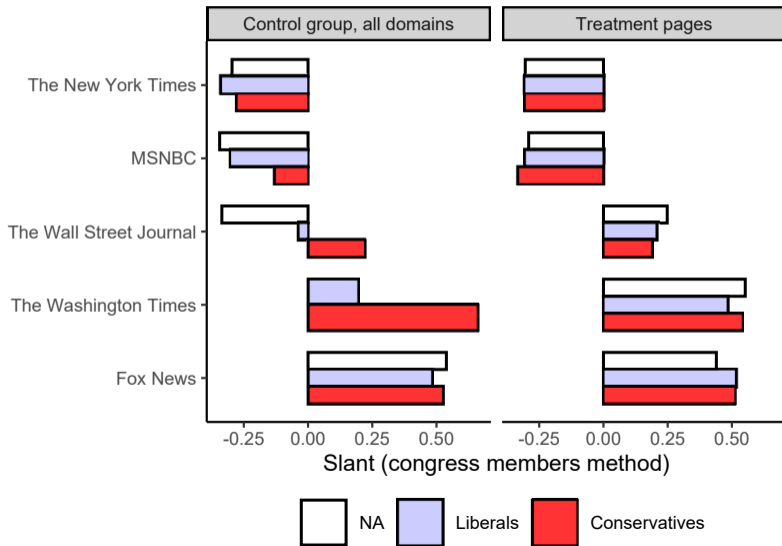
Within Outlet Heterogeneity Regressions

[◀ Back](#)

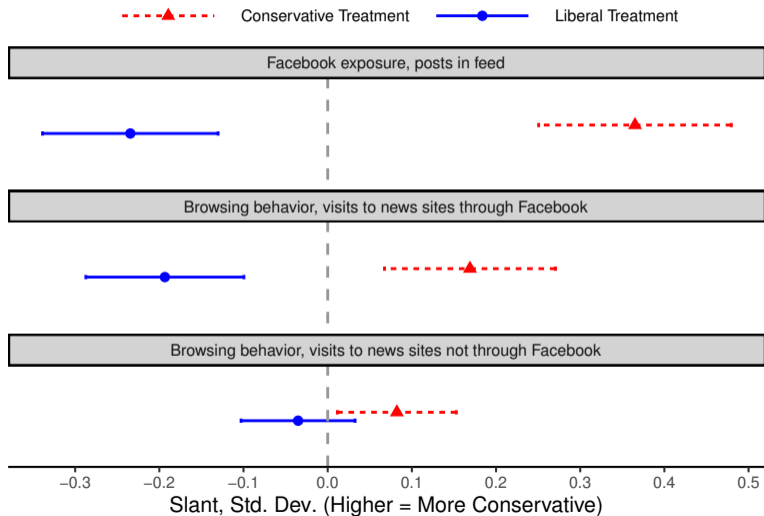
	Slant		Mean Slant
	(1)	(2)	(3)
Conservative Ideology	0.380*** (0.022)	0.134*** (0.009)	-0.008 (0.008)
Data = Potential Outlets	No	No	Yes
Outlet FE		X	X
Observations	243,214	243,214	20,307

[Plot](#)

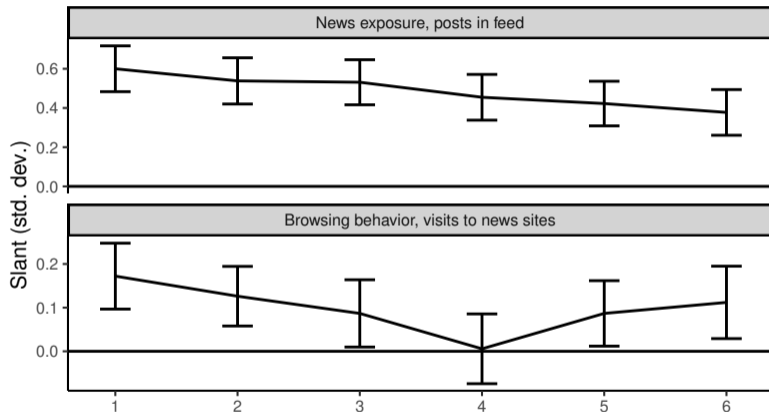
Within Outlet Heterogeneity

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Effect on Slant by Source

[◀ Back](#)

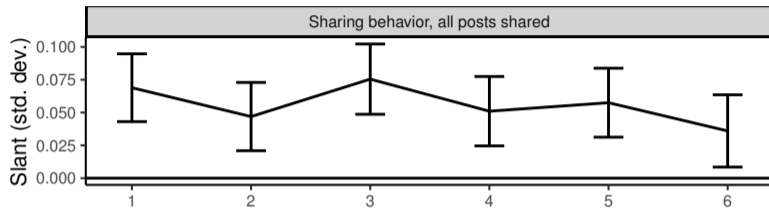
Effect on Browsing and Exposure Slant by Week

[◀ Back](#)

Participants who kept extension installed for at least 6 weeks (N = 1,596)

[By Month](#)

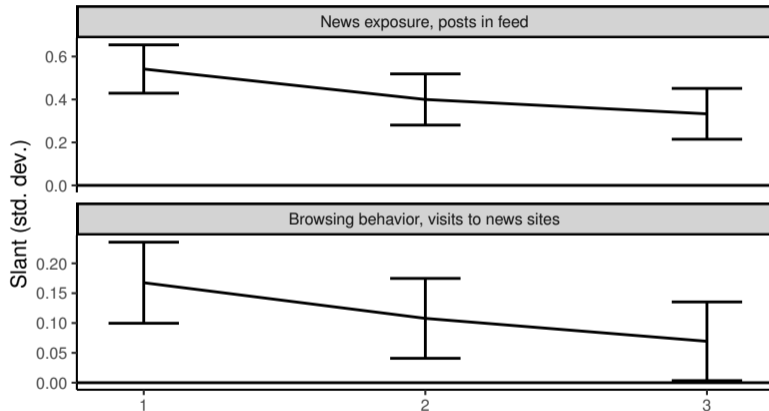
Effect on Sharing Slant by Week

[◀ Back](#)

Participants who provided permissions for at least 6 weeks (N = 29,131)

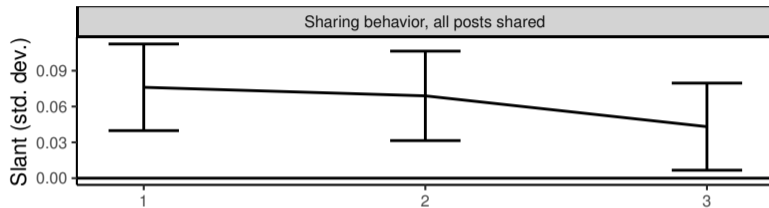
[By Month](#)

Effect on Browsing and Exposure Slant by Month

[◀ Back](#)

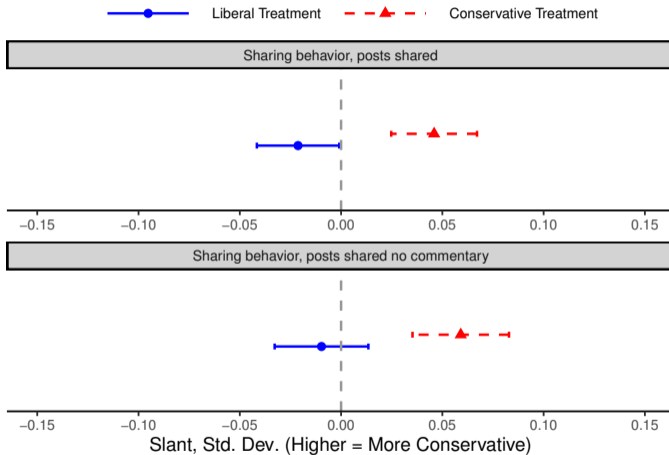
Participants who kept extension installed for at least 12 weeks (N = 1,351)

Effect on Sharing Slant by Month

[◀ Back](#)

Participants who provided permissions for at least 12 weeks (N = 9,932)

Slant - Posts Shared

[◀ Back](#)[Persistence](#)Participants in Post Sharing Subsample ($N \leq 34,592$)

Why Affective Polarization Matters

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- Decreases accountability
 - Hostility toward other party drives political behavior; Voters rarely split their votes (Abramowitz and Webster, 2016)
 - “A candidate accused of molesting teenage children is able to attract 80% of the vote from his copartisans” (Iyengar and Krupenkin, 2018)
- Partisan prejudice increases frictions (Iyengar et al., 2019)
 - Distorts labor markets, e.g., resume from opposing party less likely to receive callback (Gift and Gift, 2015)
 - Distorts beliefs, e.g. about the economy
- Contributes to government dysfunction (Levendusky, 2017)
 - Legislative gridlock
 - Less trust in government, e.g. vaccinations decrease when other party holds presidency (Krupenkin, 2019)

Specification - Belief Regressions

[◀ Back](#)

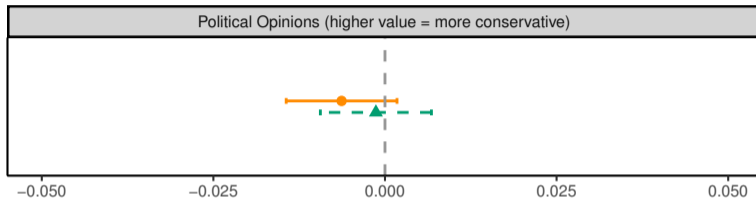
Liberal vs Conservative

- $Y_i = \beta_1 T_i^L + \beta_2 T_i^C + \alpha X_i + \varepsilon_i$
 - $T_i^L = 1$ if participant i assigned to the liberal treatment
 - $T_i^C = 1$ if participant i assigned to the conservative treatment
 - Estimate $T_i^C - T_i^L$
 - X is pre-registered controls: self-reported ideology, party affiliation, Trump approval, ideological leaning, age, age squared, gender, baseline questions similar to the outcome

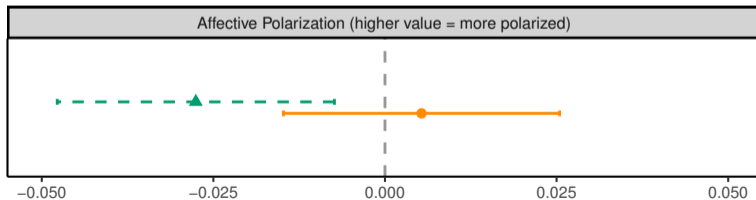
Pro vs. Counter

- $Y_i = \beta_1 T_i^P + \beta_2 T_i^A + \alpha X_i + \varepsilon_i$
 - $T_i^P = 1$ if participant i assigned to the pro-att. treatment
 - $T_i^A = 1$ if participant i assigned to the counter-att. treatment
 - Estimate $T_i^A - T_i^P$

Primary Outcomes by Treatment

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—●— Liberal Treatment - -▲- - Conservative Treatment



—●— Pro-Att. Treatment - -▲- - Counter-Att. Treatment

Media Effects Regression

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	Affective Polarization		Political Opinions	
	(1)	(2)	(3)	(4)
Pro-Att. Treatment	-0.022 (0.019)	0.005 (0.012)		
Counter-Att. Treatment	-0.055*** (0.019)	-0.028** (0.012)		
Conservative Treatment			0.010 (0.018)	-0.001 (0.005)
Liberal Treatment			-0.006 (0.018)	-0.006 (0.005)
Pro - Counter Attitudinal Treatment	0.033* (0.019)	0.033*** (0.012)	- -	- -
Conservative - Liberal Treatment	- -	- -	0.017 (0.019)	0.005 (0.005)
Controls		X		X
Observations	16,896	16,896	17,635	17,635

Robustness - Primary Outlets

[◀ Back](#)

	Opinions (1)	Opinions (2)	Opinions (3)	Polarization (4)	Polarization (5)	Polarization (6)
Conservative Treatment	0.005 (0.005)	0.006 (0.005)	0.003 (0.007)			
Counter-Att. Treatment				-0.033*** (0.012)	-0.037*** (0.013)	-0.030* (0.017)
Standard Controls	X	X	X	X	X	X
Potential Outlets FE		X			X	
Include Only Primary Outlets			X			X
Observations	11,520	11,520	6,296	11,054	11,054	5,975

Robustness - Effect on Beliefs by Subsample

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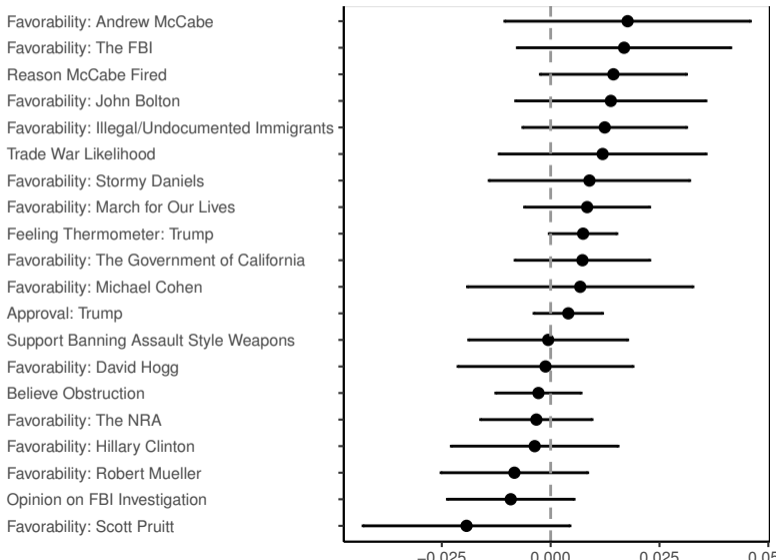
	(1)	(2)	(3)	(4)
Pro-Att. Treatment	0.005 (0.012)	0.008 (0.013)	0.015 (0.044)	0.027 (0.046)
Counter-Att. Treatment	-0.028** (0.012)	-0.027** (0.013)	-0.072* (0.043)	-0.056 (0.045)
Pro-Att. Treat. - Counter-Att. Treat	0.033*** (0.012)	0.035*** (0.013)	0.087** (0.043)	0.083* (0.045)
Controls	X	X	X	X
Sample	Endline	Endline+ Posts	Endline+ Ext	Endline+ Posts+Ext
Observations	16,896	15,647	1,241	1,151

Alternative Explanations for Null Effect

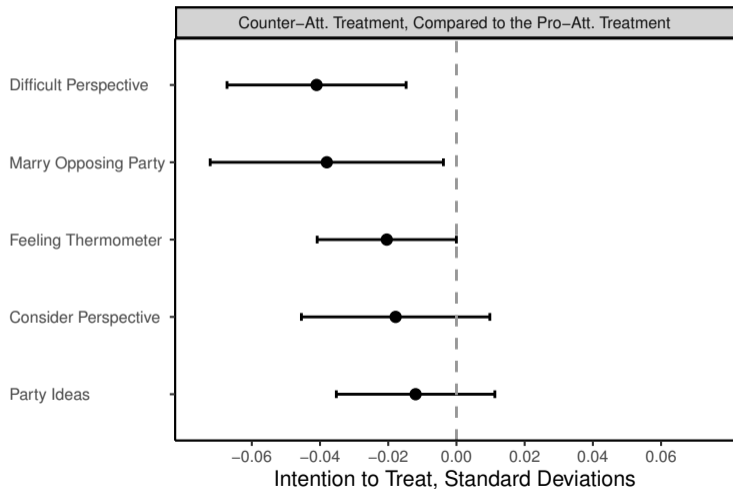
[◀ Back](#)

- Was the effect on exposure too weak?
 - Combined ITT effects of treatments equals 36% of gap between feeds of liberals and conservative (TOT 47%)
 - Stronger among posts shared by outlets [Slant Dist.](#)
 - Participants noticed the change [Outcomes, User*Outlet](#)
- Masks important heterogeneity?
 - No evidence for backlash effect [By Treatment and Ideology](#)
 - Weak effect on all index measures [Political Opinion Measures](#)

Political Opinion Measures

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Affective Polarization Measures

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Polarization Measures Regression

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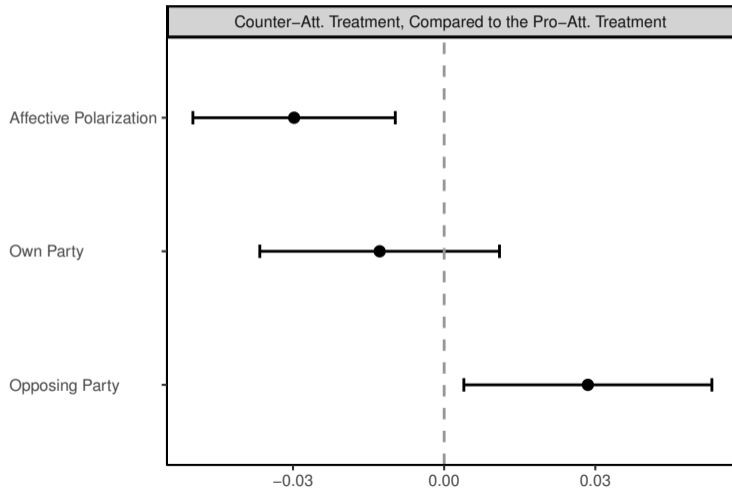
	Index (1)	Feeling Thermometer (2)	Difficult Perspective (3)	Consider Perspective (4)	Party Ideas (5)	Marry Opposing Party (6)
Counter-Att. Treatment	-0.028** (0.012)	-0.006 (0.012)	-0.046*** (0.016)	-0.012 (0.017)	0.0002 (0.014)	-0.052** (0.021)
Pro-Att. Treatment	0.005 (0.012)	0.015 (0.012)	-0.005 (0.015)	0.006 (0.017)	0.012 (0.014)	-0.014 (0.021)
Counter - Pro	-0.033*** (0.012)	-0.020* (0.012)	-0.041** (0.016)	-0.018 (0.017)	-0.012 (0.014)	-0.038* (0.021)
Observations	16,896	16,331	16,822	16,816	16,896	10,466

Polarization Excluding One Measure

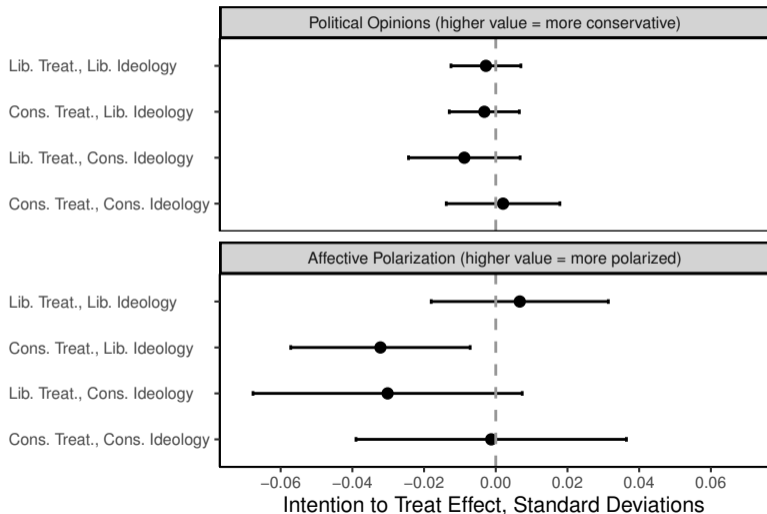
[◀ Back](#)

	(1)	(2)	(3)	(4)	(5)	(6)
Pro-Att. Treatment	0.005 (0.012)	0.001 (0.013)	0.008 (0.013)	0.005 (0.012)	0.002 (0.013)	0.010 (0.012)
Counter-Att. Treatment	-0.028** (0.012)	-0.033** (0.013)	-0.018 (0.013)	-0.029** (0.012)	-0.035*** (0.013)	-0.020* (0.012)
Pro - Counter	0.033*** (0.012)	0.034** (0.014)	0.025** (0.013)	0.034*** (0.012)	0.038*** (0.013)	0.030** (0.012)
Excluded Measure		Feeling Thermometer	Difficult Perspective	Consider Perspective	Party Ideas	Marry Opposing Party
Observations	16,896	16,896	16,896	16,896	16,895	16,896

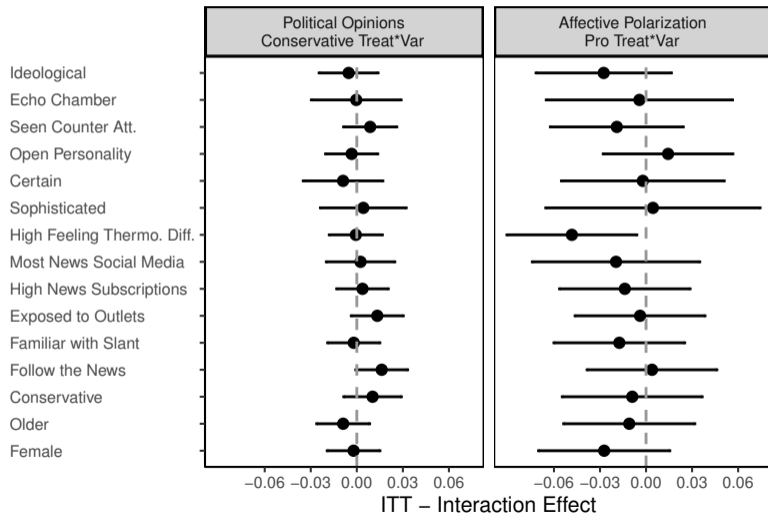
Polarization - Own vs Other Party

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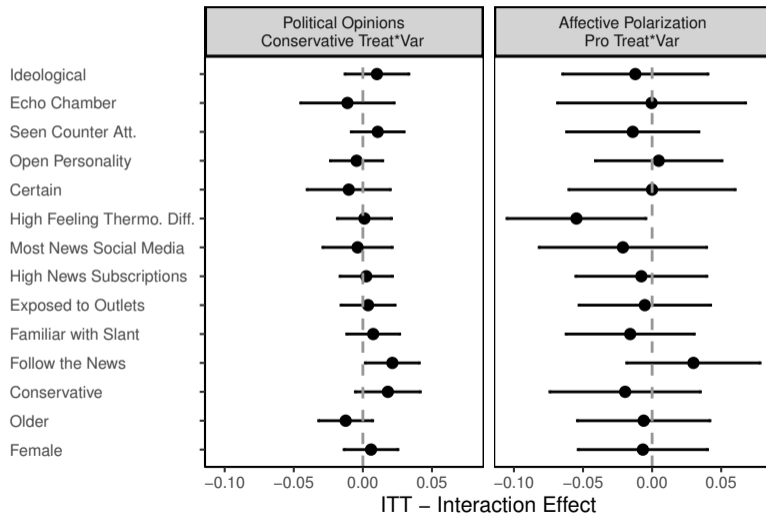
Treatment and Ideology

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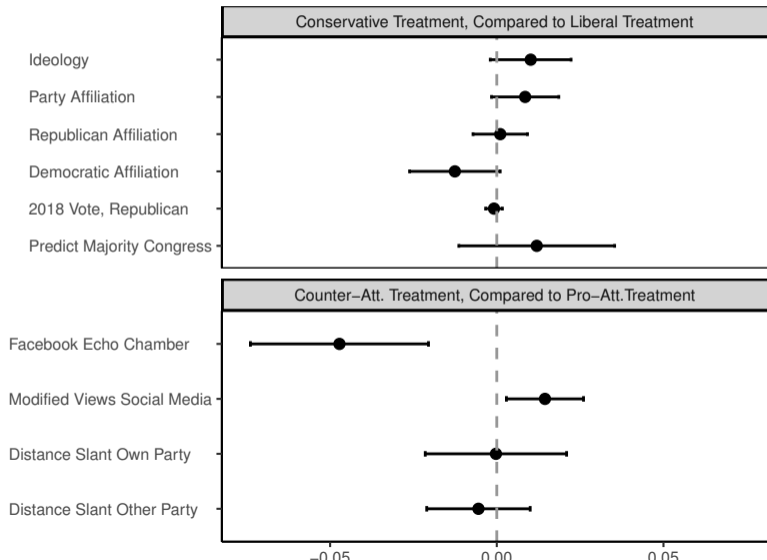
Heterogeneity

[◀ Back](#)
[Main Results](#)


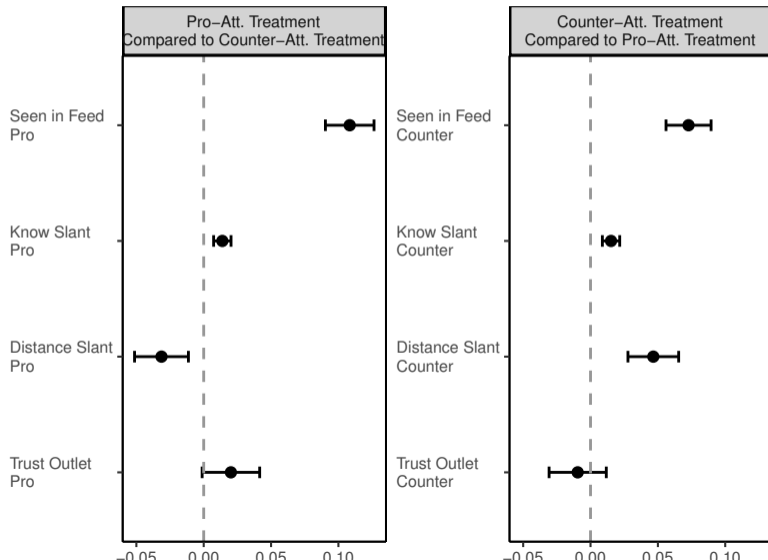
Heterogeneity Using the Same Regression

[Main Results](#)


Other Outcomes

[Main Results](#)
[Mechanisms](#)


Outcomes, User by Outlet

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Knowledge

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	Heard Michael Cohen (1)	Heard Clark Shooting (2)	Heard Louis Farrakhan (3)	Heard Clinton Speech (4)	Correct Russian Influence (5)	Correct Wall Built (6)	Correct Trump Target (7)	Correct Tax Cut (8)
Liberal Treatment	-0.004 (0.006)	0.007 (0.007)	-0.004 (0.006)	0.008 (0.008)	0.002 (0.005)	0.016* (0.009)	-0.003 (0.009)	-0.001 (0.006)
Conservative Treatment	-0.002 (0.006)	0.002 (0.007)	-0.002 (0.006)	0.019** (0.008)	0.010* (0.005)	0.0001 (0.009)	-0.007 (0.009)	0.0004 (0.006)
Cons. Treat - Lib. Treat	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	-0.02* (0.01)	-0.00 (0.01)	0.00 (0.01)
Controls	X	X	X	X	X	X	X	X
Expected Effect	Lib Treat	Lib Treat	Cons Treat	Cons Treat	Lib Treat	Lib Treat	Cons Treat	Cons Treat
Observations	17,635	17,431	17,635	17,464	16,167	13,872	12,141	15,655

Knowledge - Exposure

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	Michael Cohen (1)	Clark Shooting (2)	Louis Farrakhan (3)	Clinton Speech (4)
Liberal Treatment	2.558*** (0.820)	1.172*** (0.350)	0.161 (0.116)	0.041 (0.041)
Conservative Treatment	0.554 (0.531)	0.080 (0.260)	0.398*** (0.103)	0.077** (0.032)
Cons. Treat - Lib. Treat	-2.00** (0.81)	-1.09*** (0.31)	0.24* (0.13)	0.04 (0.04)
Controls	X	X	X	X
Expected Effect	Lib. Treat	Lib. Treat	Cons. Treat	Cons. Treat ¹⁰

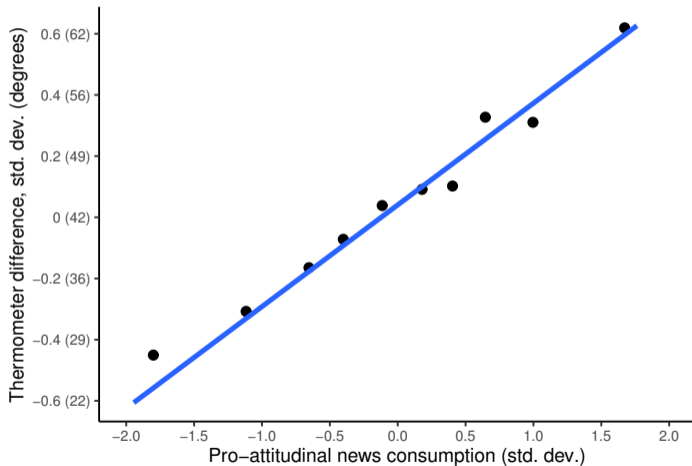
Balanced Facebook Feed

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slantBet_FBScaled	0.039 (0.035)
First Stage F-Stat	60.31
Control Difference in Slant: Conservative - Liberal	1.675
Effect of Switching Feeds	0.065
Control Difference in Pol. Opinions: Conservative - Liberal	1.737
Effect of Switching Feed, Share of Control Group	4%
Observations	1,080

Counter-Att. share in feed is the standardized share of posts from counter-attitudinal outlets among all pro and counter-attitudinal posts, between the baseline and followup survey. The instrument is whether the treatment matched the participant's ideology.

Pro-Att. News Correlated With Polarization

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Source: Binned scatter plot of respondent data from the 2016 American National Election Survey. Pro attitudinal news consumption defined as $\text{slant} \times \text{sign}(\text{ideology})$, where ideology is positive for conservative and negative for liberals. Slant based on Bakshy et al. (2015). The feeling thermometer in this survey refers to liberals and conservative (not Democrats and Republicans)

Affective Polarization Elasticity

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	IV Affective Polarization	
	(1)	(2)
FB Counter-Att. Share, Std. Dev.	-0.130* (0.067)	
FB Congruence Scale, Std. Dev.		0.105* (0.057)
Controls	X	X
First Stage F	65.1	65.22
Observations	1,072	1,072

Counter-Att. Share in Feed is the standardized share of posts from counter-attitudinal outlets among all pro and counter-attitudinal posts, between the baseline and followup survey. FB Feed Slant*Ideology is the participant's Facebook feed mean slant, multiplied by -1 for liberals. The instrument is whether the treatment matched the participant's ideology.

Affective Polarization - Control Group

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	OLS Affective Polarization (1)	OLS (2)
FB Counter-Att. Share, Std. Dev.	-0.385*** (0.052)	
FB Congruence Scale, Std. Dev.		0.407*** (0.054)
Data	Control Group	Control Group
Observations	352	352

Counter-Att. Share in Feed is the standardized share of posts from counter-attitudinal outlets among all pro and counter-attitudinal posts, between the baseline and followup survey. FB Feed Slant*Ideology is the participant's Facebook feed mean slant, multiplied by -1 for liberals.

Counterfactual Regressions

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	IV			
	Affective Pol., Std. Dev. (1)	Affective Pol., Std. Dev. (2)	Feeling Thermo., Degrees (3)	Feeling Thermo., Degrees (4)
FB Counter-Att. Share	-0.565* (0.289)		-11.927 (7.747)	
FB Congruence Scale		0.479* (0.258)		10.264 (6.984)
Controls	X	X	X	X
Control Group: Counter Share	0.17		0.17	
Effect of Counter Share = 0.5	-0.19		-3.94	
Control Group: Congruence		0.33		0.33
Effect of Congruence Scale = 0		-0.16		-3.43
Control Group: Diff in Counter Share	0.02		0.02	
Effect of Equating Counter Share	-0.01		-0.24	
Control Group: Diff in Congruence		-0.06		-0.06
Effect of Equating Congruence		-0.03		-0.62
Observations	1,072	1,072	1,031	1,031

Estimating Differential Exposure

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1. $TotalSub_i = S_{\Delta} ProTreat_i + \varepsilon_i$

- $TotalSub_i$ is the number of subscriptions of participant i
- $ProTreat_i$ is whether i was assigned to the pro-att. treatment

2. $SharePosts_{ij} = P_C * Sub_{ij} + P_{\Delta} * Sub_{ij} \times Pro_{ij} + \delta * Pro_{ij} + \varepsilon_{ij}$

- Pool two groups of outlets * individuals
- $SharePosts_{ij}$ is share of posts from group j (four pro/counter att. outlets) among all posts viewed by i
- Sub_{ij} is the number of subscriptions of i to outlets in group j
 - Instrumented by whether outlets j were offered to i
- Pro_{ij} is whether j is pro-attitudinal with respect to i
- Std errors clustered at the participant level

3. $TotalPosts_i = T_{\Delta} ProTreat_i + X_i + \varepsilon_i$

- $TotalPosts_{ij}$ is the number of posts observed by i in the feed

Exposure Gap Regression

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	Subscriptions	FB Usage: Total Posts Observed	Platform Algorithm: Share of Posts
	OLS	OLS	IV
	(1)	(2)	(3)
Pro-Att. Treatment	0.505*** (0.086)	248.765* (150.666)	
Subscriptions			0.966*** (0.093)
Subscriptions * Pro-Att.			0.460*** (0.162)

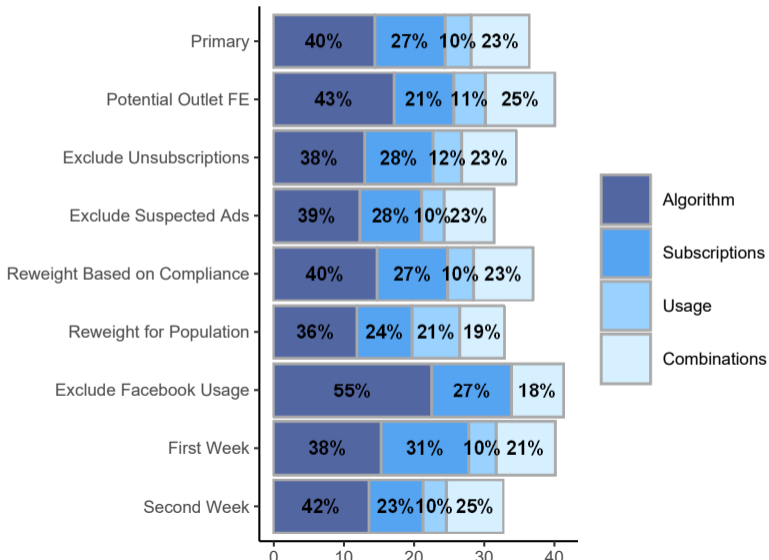
Unit

Participant

Participant

Participant by

Alternative Decompositions

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Customized News Common

[◀ Back](#)

THE PUBLIC EDITOR

A 'Community' of One: The Times Gets Tailored



Illustration by Jeffrey Henson Soles, photograph by Herbert Geitz/The Life Picture Collection Creative, via Getty Images

NYT - Suggested Articles

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Mechanisms

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What drives affective polarization?

- Inconsistent explanation
 - Persuasion? Effect on opinions did not change
 - Americans incorrectly perceive other party's position (Yudkin et al., 2019). Did not learn the other side is less extreme [Regression](#)
 - Affected by change in negative coverage? Attitudes driven by effect of counter-att. treatment on opposing party [Regression](#)
- Possible explanations
 - Increased tribalism (Mason, 2015)? Very small effect on partisan identification (not sig.)
 - Understood the other side's arguments even if continued to disagree with their importance

Theoretical Framework - Affective Polarization

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- **How do individual forms attitudes toward parties?**
 1. Distance in political opinions (Rogowski and Sutherland, 2016)
 - ↓ Divergence in opinions → ↓ polarization
 2. Function of whether opinions can be rationalized
 - ↑ Understand other party's arguments → ↓ polarization

Theoretical Framework - Affective Polarization

[◀ Back](#)

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● Example

- Political opinions are weighted averages of beliefs
- Weights when forming opinion on a carbon tax
 - Rep. care about electricity prices
 - Dem. care about emissions
- Exposure to WSJ → Democrat learns tax increases prices
 - ↑ Rationalize Rep. opinion → affective polarization ↓
 - Political opinion does not change

Overview

- Outlets report the news with an ideological slant
- Consumers read the reports and update their beliefs
- Changes in beliefs affect
 - Political opinions
 - Attitudes toward parties
- Political opinions - weighted average of beliefs
- Attitudes - compare two theories
 1. Distance in political opinions determines attitude
 2. “Unreasonable” opinions determines attitude

Persuasion Framework

Setting: Consumer learning from biased news (DellaVigna and Kaplan, 2007)

- Consumer i has a prior θ_i^0 on state of the world with precision h_i

$$\theta_i \sim (\theta_i^0, \frac{1}{h_i})$$

- Consumer's political opinion γ is a weighted average of beliefs θ

$$\gamma_i = \sum_k w_{ik} \theta_{ik} \text{ where } w_{ik} \text{ is the weight } i \text{ places on topic } k$$

- Outlet j reports a signal on θ with bias b

$$r_j = s + b_j \text{ where } s \sim N(\theta^*, \frac{1}{h_S}) \text{ and } \theta^* \text{ is the true state}$$

- i formulates a posterior θ_i^1 , updates political opinion

$$\theta_i^1 \sim N\left(\frac{h_i \theta_i^0 + h_S f(r_j, b_j)}{h_i + h_S}, \frac{1}{h_i + h_S}\right); \gamma_i^1 = \sum_k w_{ik} \theta_{ik}^1$$

Terms and Example

Consider a bill to address climate change

- **Political opinions** $\gamma_i = \sum_k w_{ik}\theta_{ik}$: i 's support for the bill
- **Beliefs** $\theta_{i,k}$
 - $\theta_{i,emissions}$: effect of bill on emissions
 - $\theta_{i,costs}$: effect of bill on electricity costs
- **Weights** $w_{i,k}$: priority placed on beliefs, common information
 - $w_{Dem,emissions} > w_{Dem,costs}$
 - $w_{Rep,costs} > w_{Rep,emissions}$
- **Attitudes** A_{ip} : Attitude of consumer i toward party p
 - Assume A_{ip} is a linear function of difference between p 's opinion and benchmark opinion: $g(\gamma_p - \hat{\gamma}_{ip})$

Political Distance → Affective Polarization

- **Political distance determines attitude:** $\hat{\gamma}_{ip} = \sum_k w_{ik} \theta_{ik}$

$$A_{ip} = g\left(\sum_k w_{pk} \theta_{pk} - \sum_k w_{ik} \theta_{ik}\right)$$

- $\theta_{ik}^0 \rightarrow \theta_{ik}^1 \Rightarrow$ change in attitude of i toward p :

$$\Delta A_{ip} = g\left(\sum_k w_{ik} (\theta_{ik}^1 - \theta_{ik}^0)\right)$$

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- Predictions
 - Beliefs affect attitudes only through i 's political opinions

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- Predictions
 - Beliefs affect attitudes only through i 's political opinions
 - Weights of individual i matter

Unreasonable Opinion → Affective Polarization

- **“Unreasonable” opinion determines attitude:** $\hat{\gamma}_{ip} = \sum_k w_{pk} \theta_{ik}$

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- $\theta_{ik}^0 \rightarrow \theta_{ik}^1 \Rightarrow$ change in attitude of i toward p :

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- Predictions
 - Can differentially update attitudes and opinions
 - Weights of individual i determine opinions
 - Weights of party p matter determine attitudes
 - Intuition: understand party's argument but do not agree with its importance

Unreasonable Opinion → Affective Polarization

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- Predictions

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- Weights of party p matter determine attitudes
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Test: Own vs Opposing Party

- Assume outlets act as delegates

Cover issues their consumers place higher weights on \Rightarrow

- Pro-att. outlets more likely to cover issue j when $W_{own,j} > W_{opposing,j}$
- Counter-att. outlets more likely to cover issue j when $W_{opposing,j} > W_{own,j}$

Test: Own vs Opposing Party

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-
- *Political distance* predictions
 - Pro-att. treatment affects attitudes toward opposing party
 - *Unreasonable opinion* prediction
 - Counter-att. treatment affects attitudes toward opposing party

Own vs Other Opposing Regression

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	Attitude Own Party (1)	Attitude Opposing Party (2)
Pro-Att. Treatment	0.008 (0.013)	-0.003 (0.014)
Counter-Att. Treatment	0.001 (0.014)	0.031** (0.014)
Pro - Counter	0.007 (0.014)	-0.035** (0.014)
Observations	16,896	16,896

Attempts to Mitigating Polarization

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March 23, 2017

Right and Left: Partisan Writing You Shouldn't Miss

Read about how the other side thinks. We have collected political writing from around the web and across ideologies.

By ANNA DUBENKO



The AllSides Mission:

Free people from filter bubbles so they can better understand the world and each other

PolitEcho

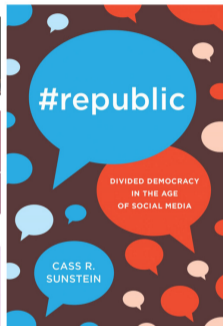
Is your news feed a bubble?

FLIPFEED

Step into someone else's Twitter feed

Burst your bubble

The Guardian's weekly guide to conservative articles worth reading to expand your thinking



Escape Your Bubble
4,799
Thoughtful article on the U.S. Working Class #Republicans

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